

# Potential Outcomes

Brady Neal

[causalcourse.com](https://causalcourse.com)

**What are potential outcomes?**

**The fundamental problem of causal inference**

**Getting around the fundamental problem of causal inference**

**A complete example with estimation**

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A complete example with estimation

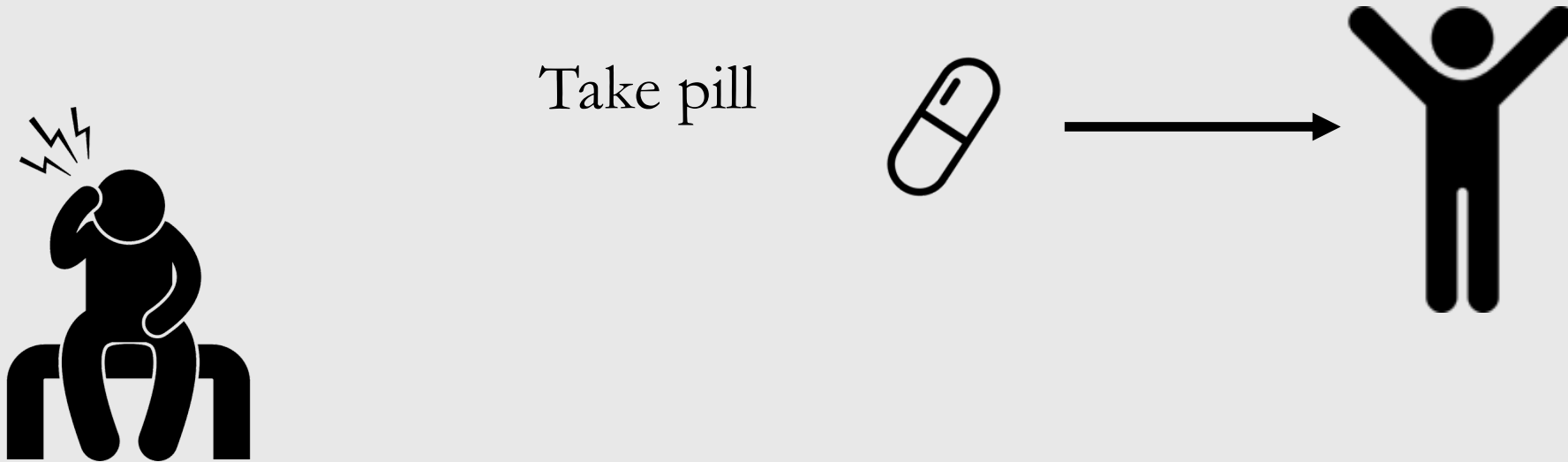
# Potential outcomes: intuition

Inferring the effect of treatment/policy on some outcome



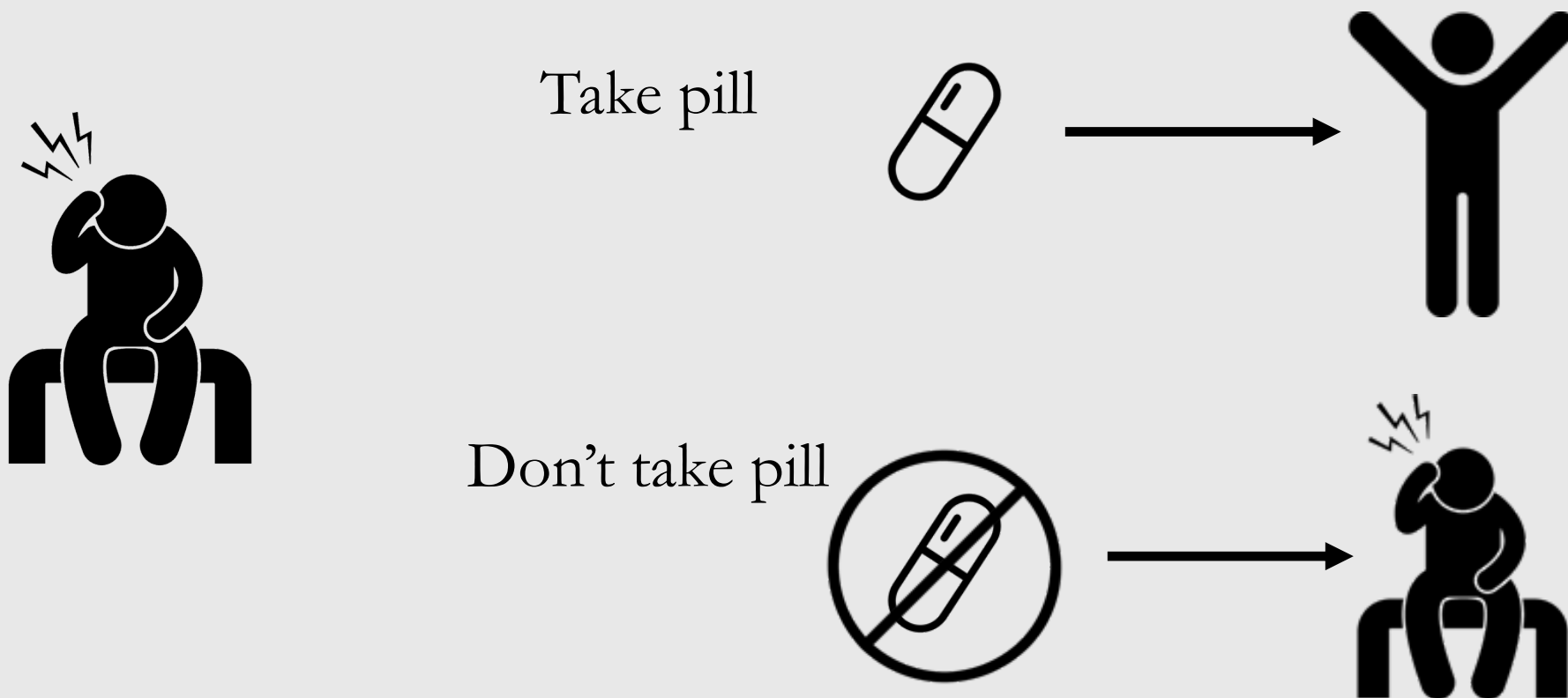
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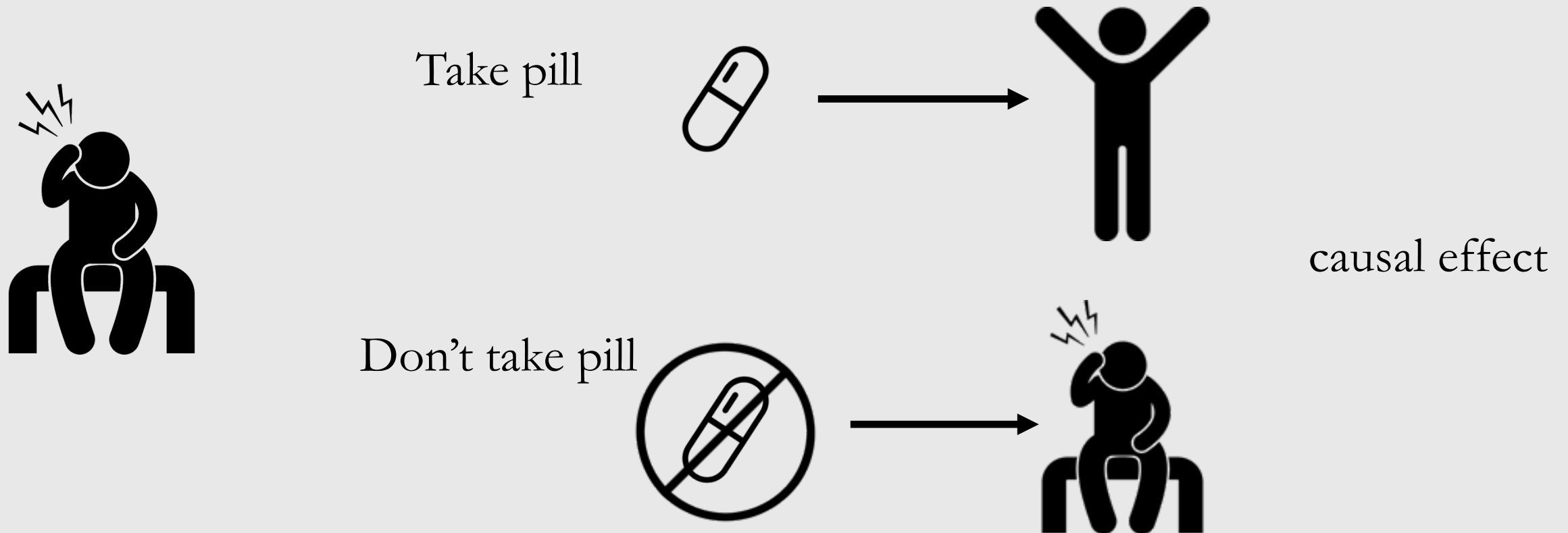
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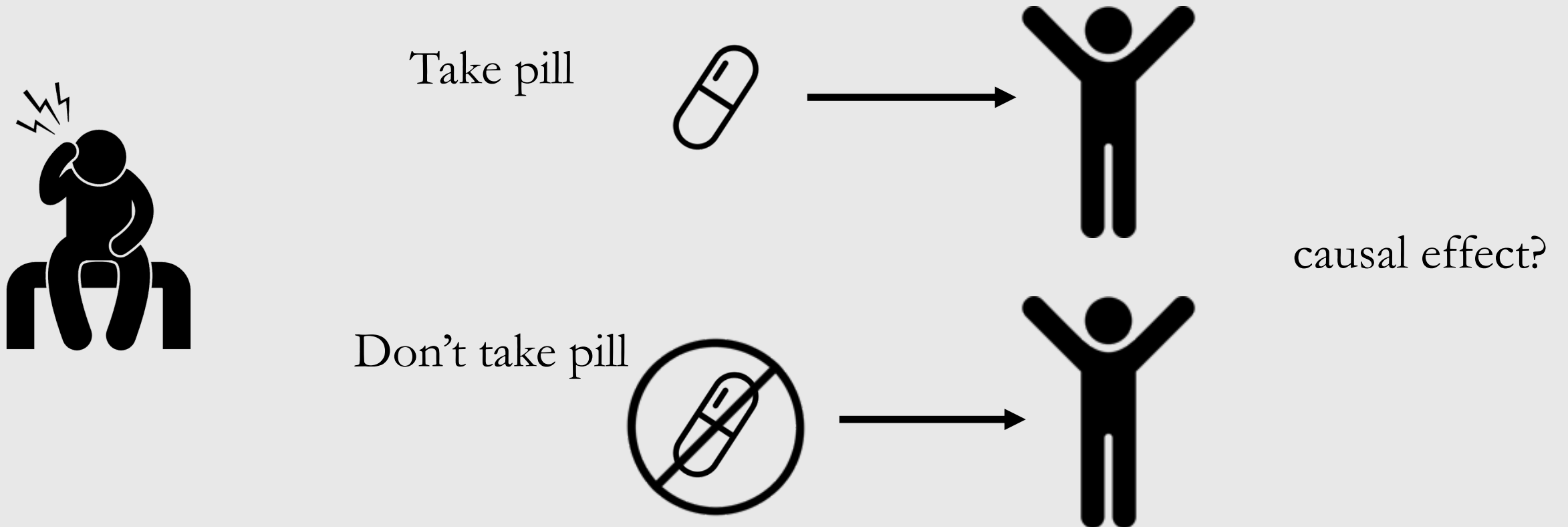
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# Potential outcomes: intuition

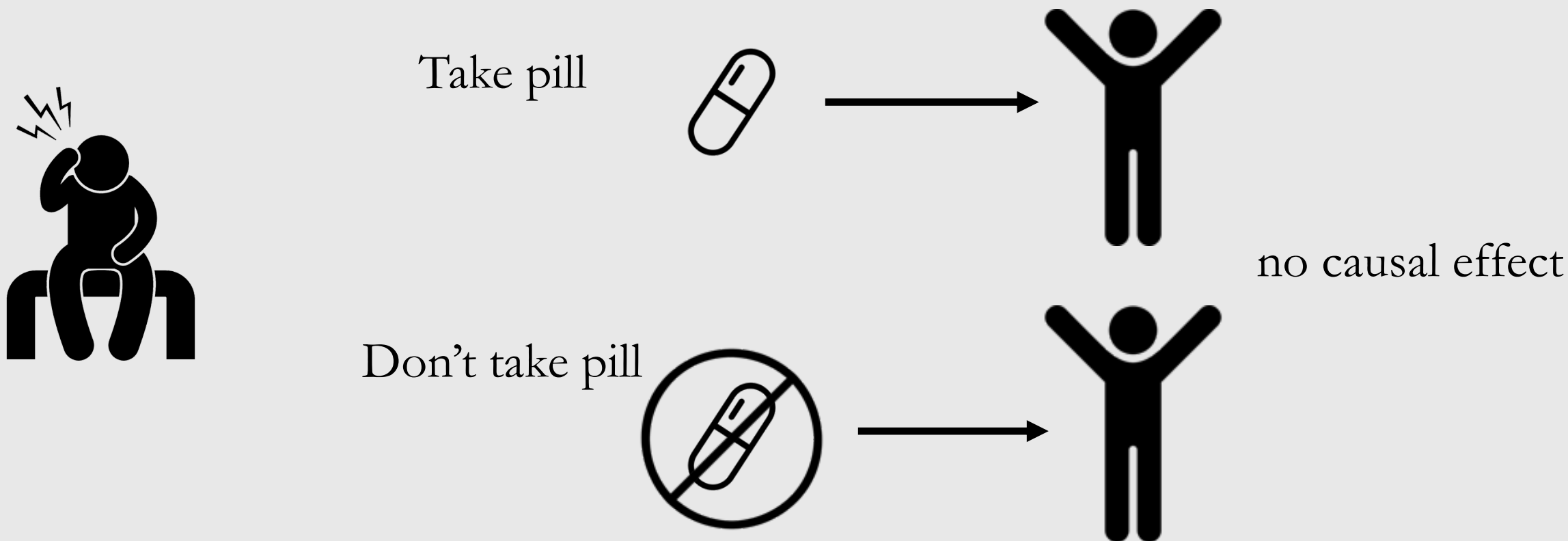
Inferring the effect of treatment/policy on some outcome





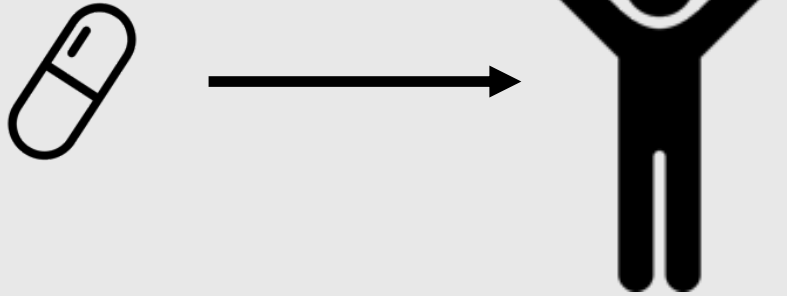
# Potential outcomes: intuition

Inferring the effect of treatment/policy on some outcome



# Potential outcomes: notation

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

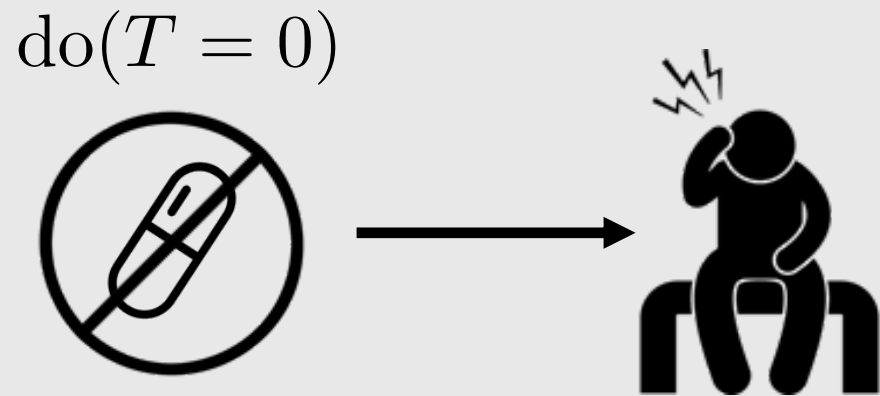
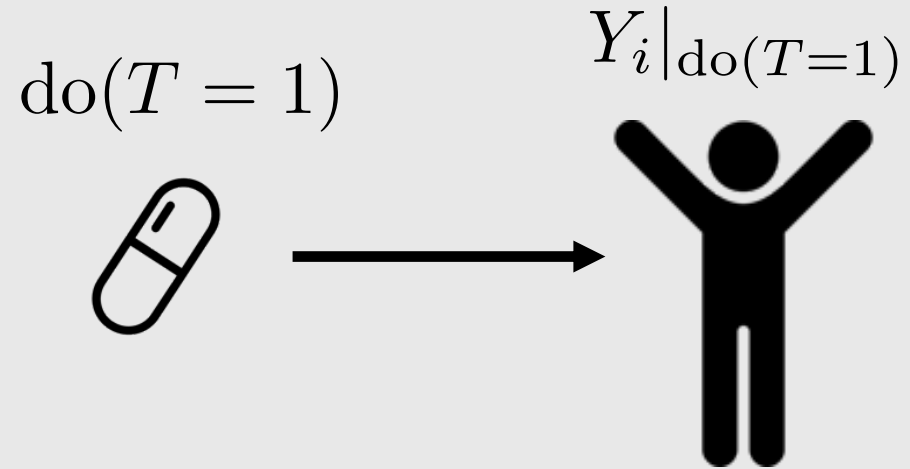


$\text{do}(T = 0)$



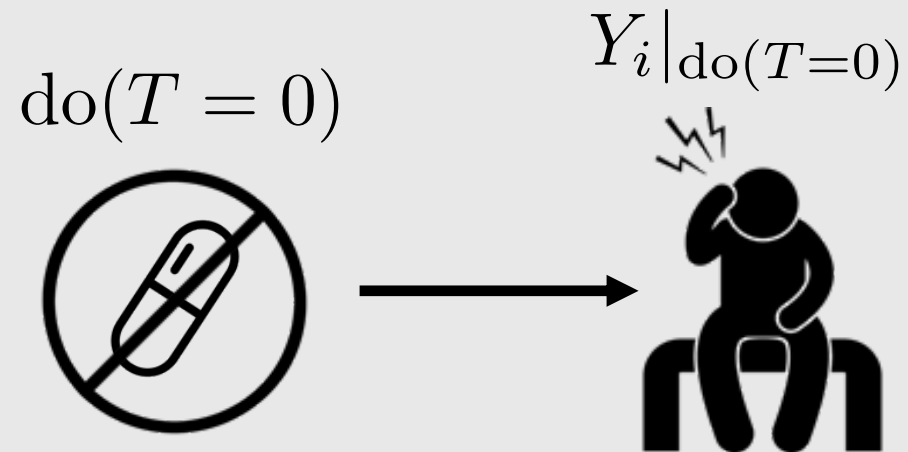
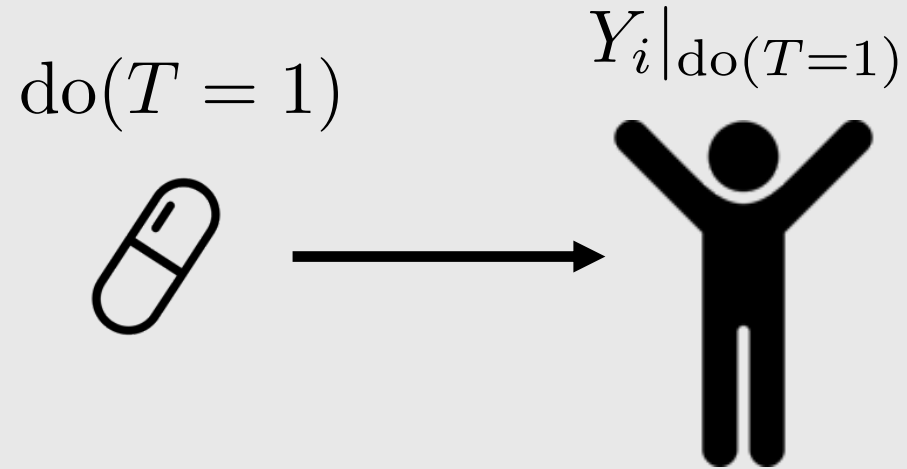
$T$  : observed treatment  
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# Potential outcomes: notation



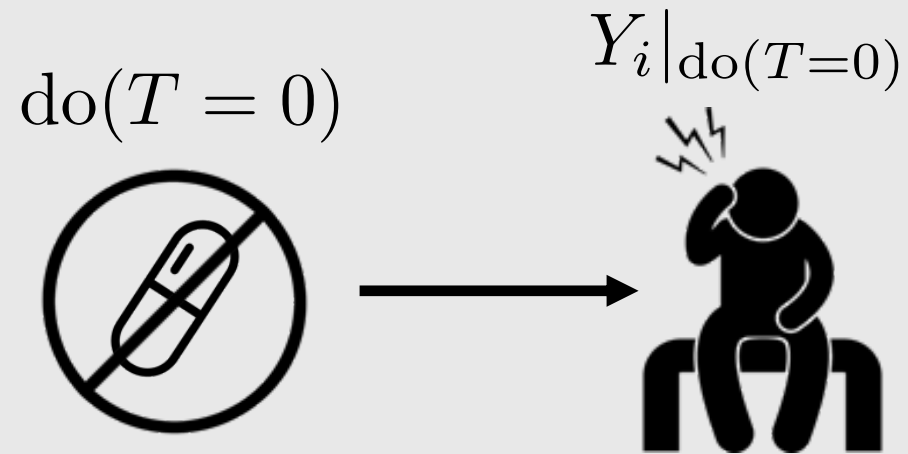
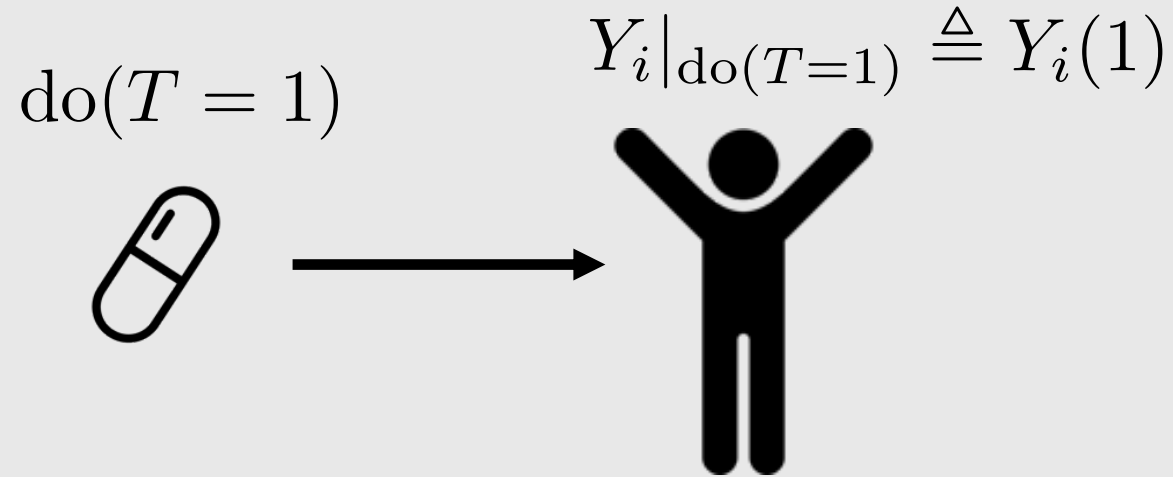
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# Potential outcomes: notation



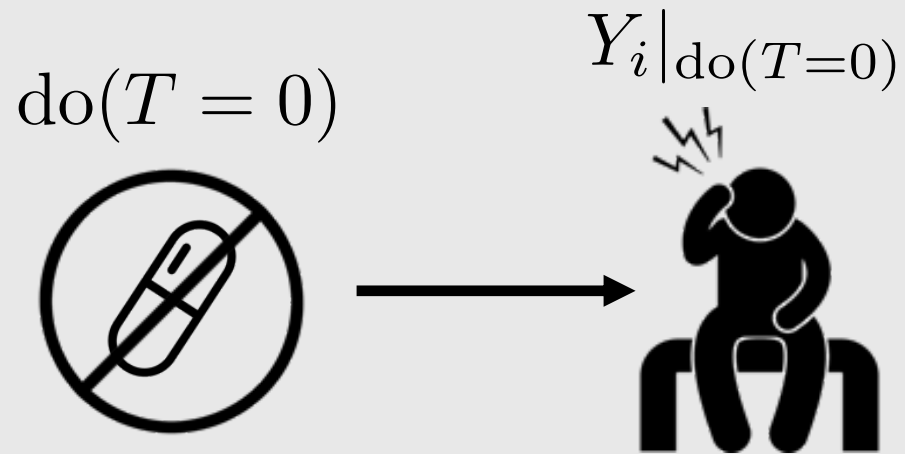
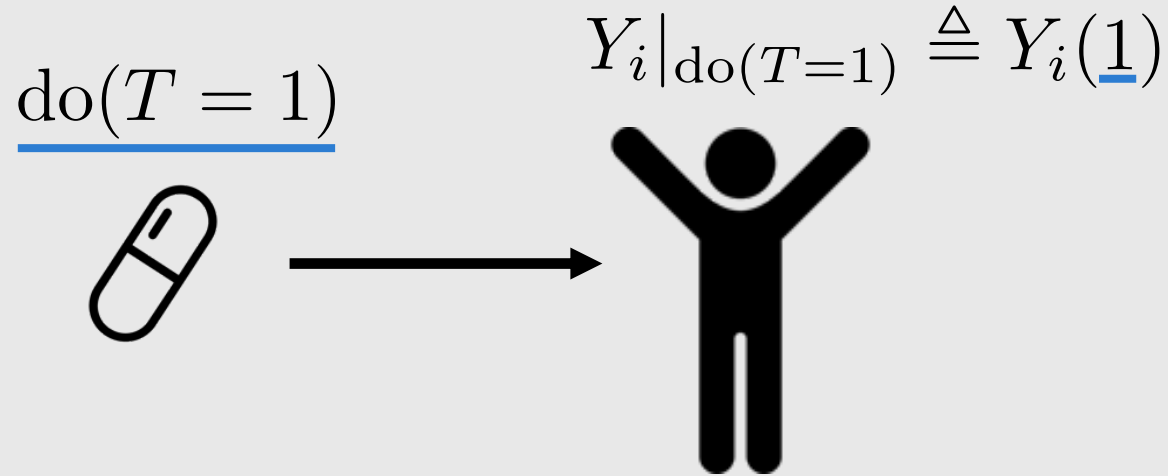
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# Potential outcomes: notation



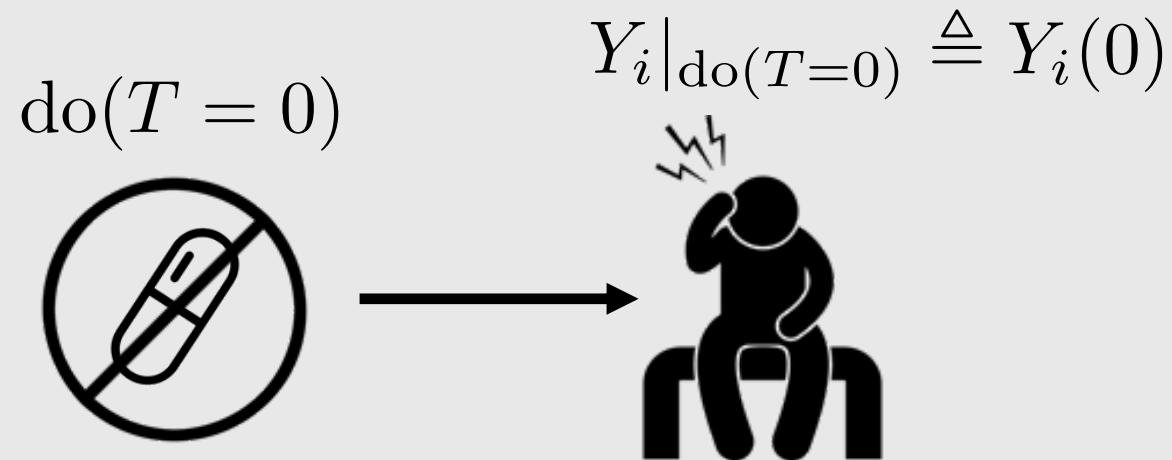
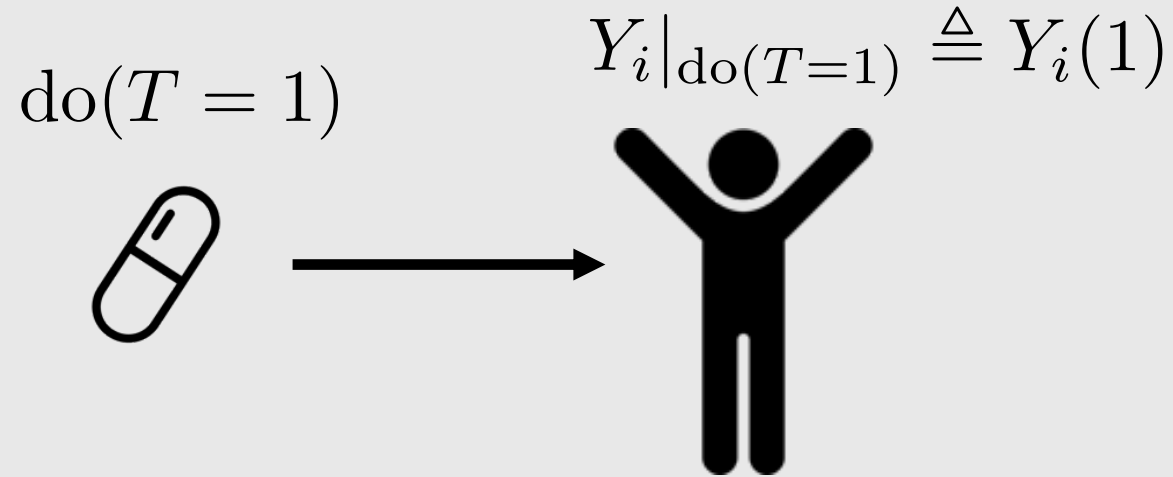
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# Potential outcomes: notation



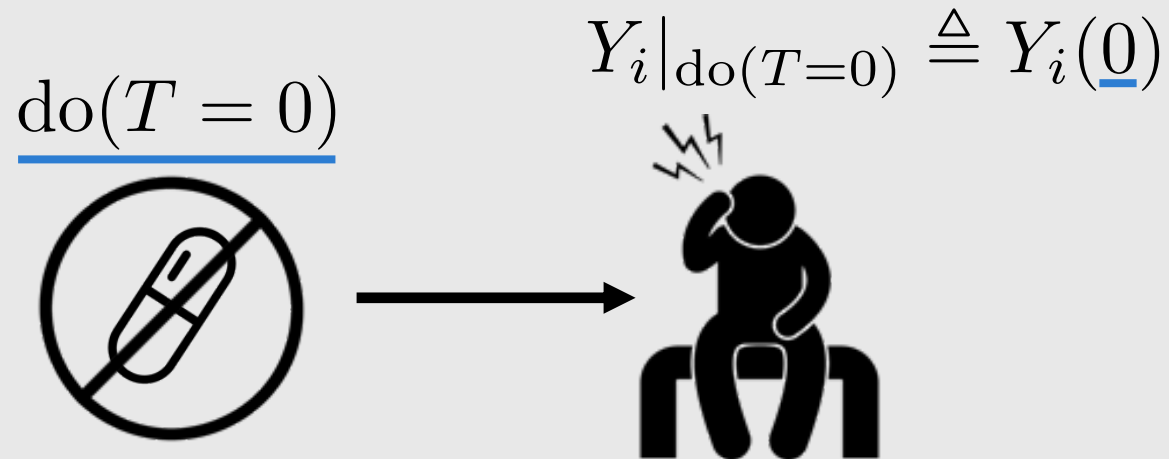
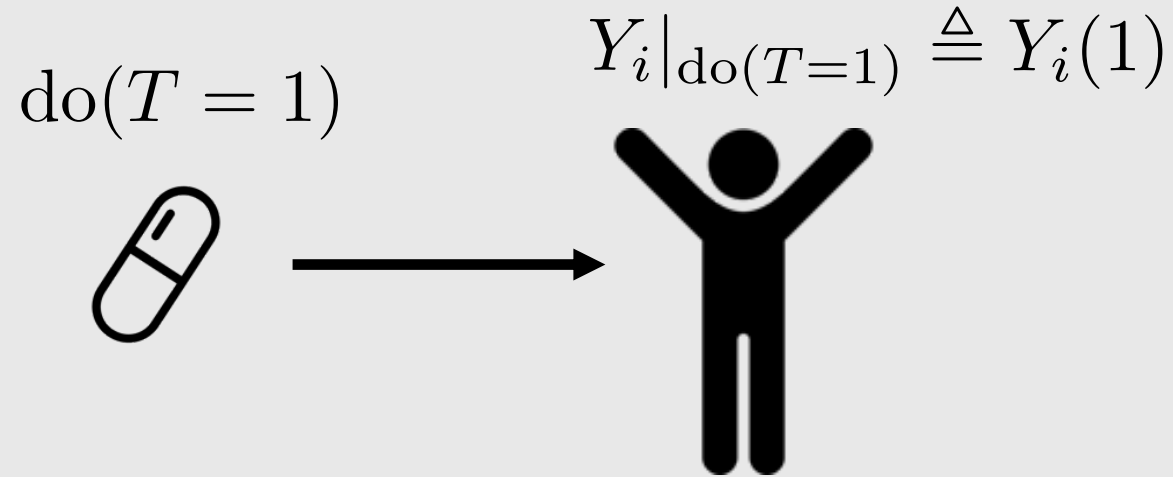
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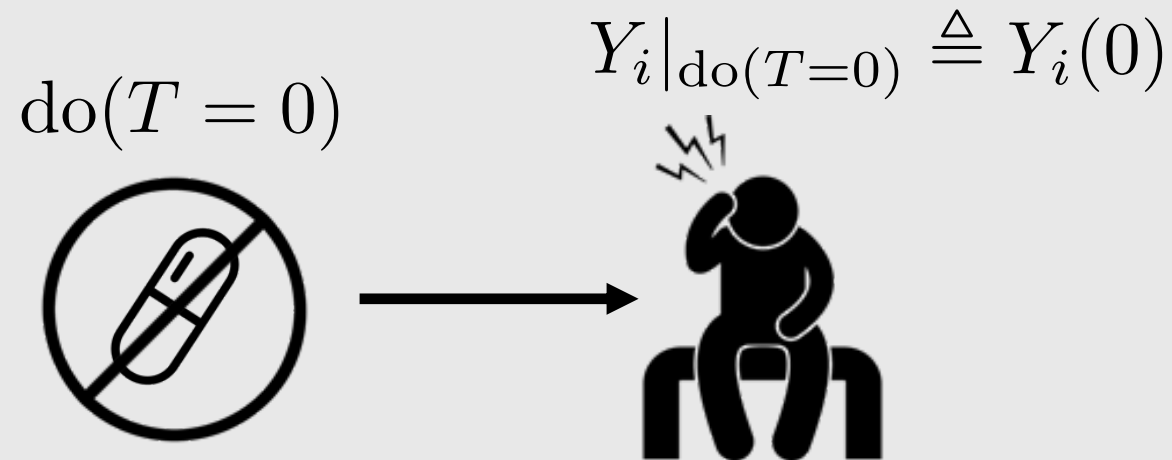
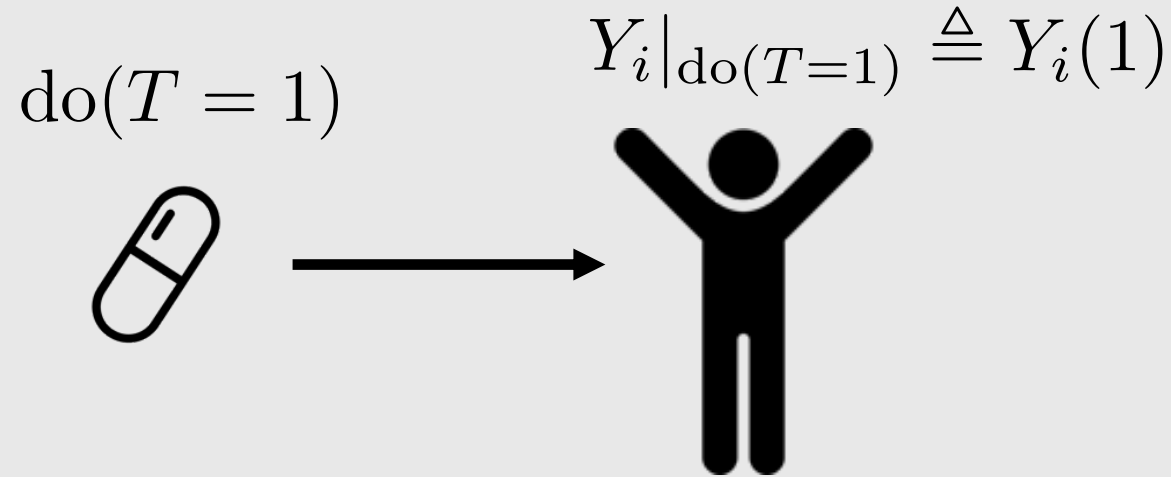
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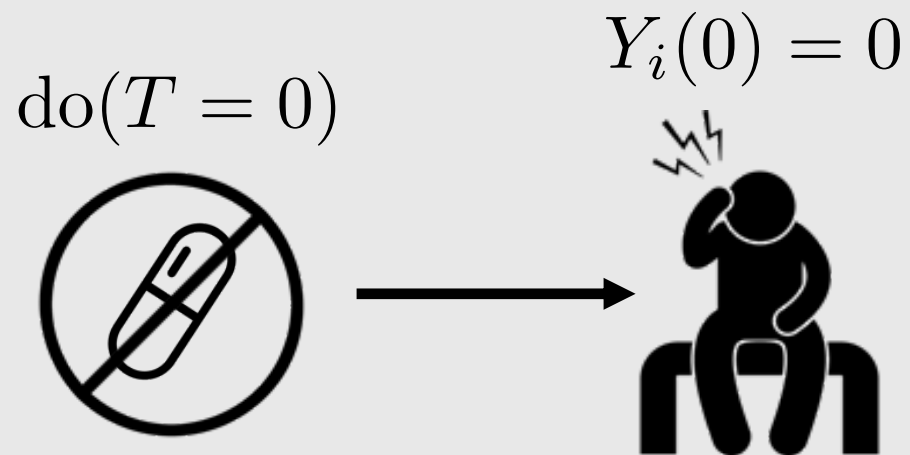
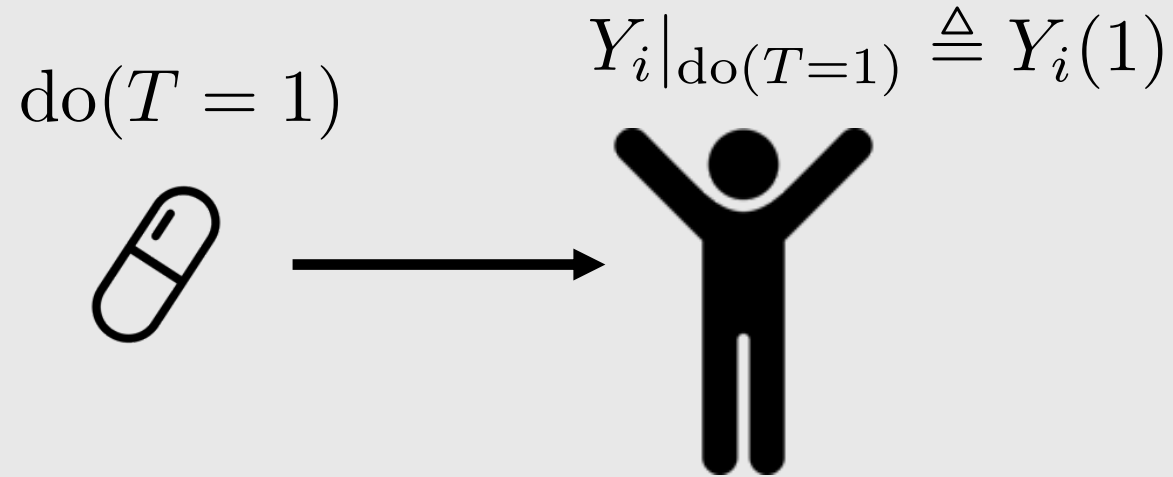
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**Causal effect**  
 $Y_i(1) - Y_i(0)$

# Potential outcomes: notation

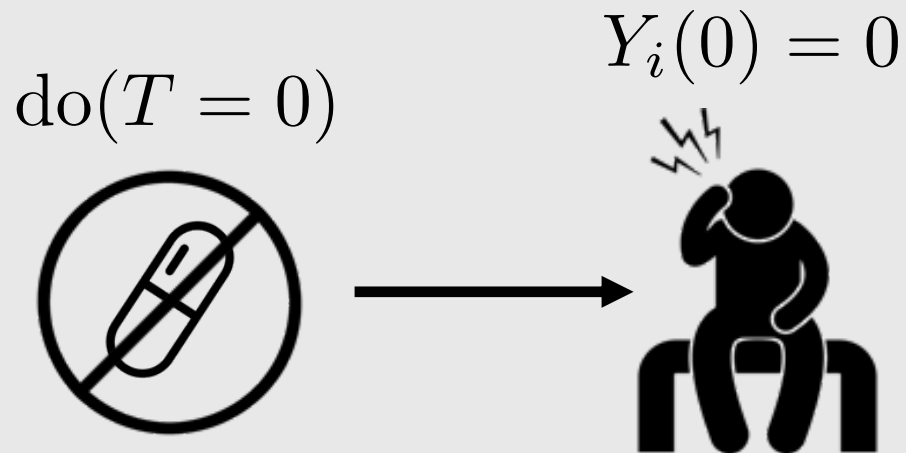
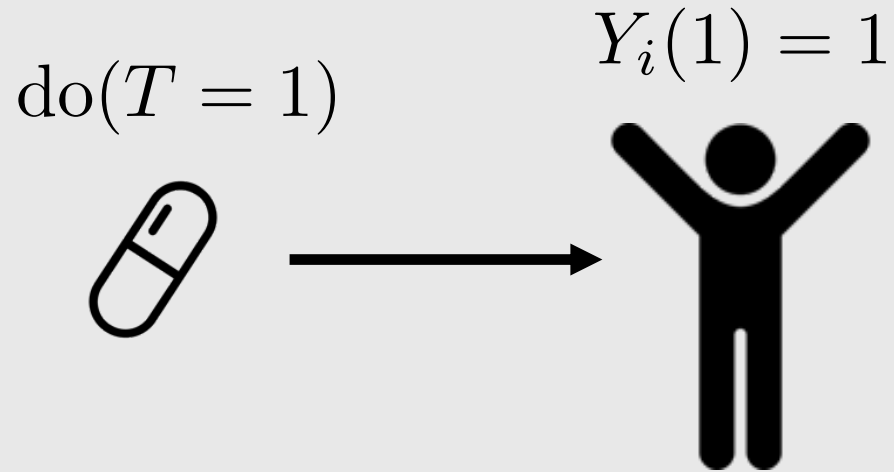


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**Causal effect**

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

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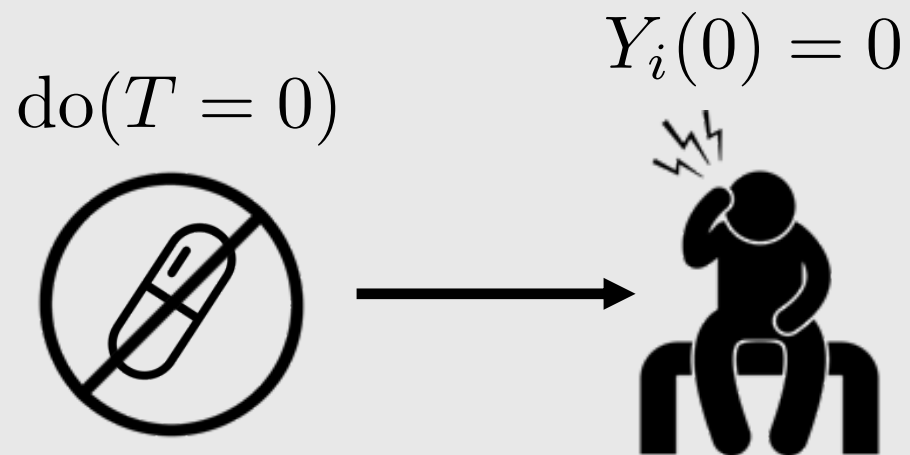
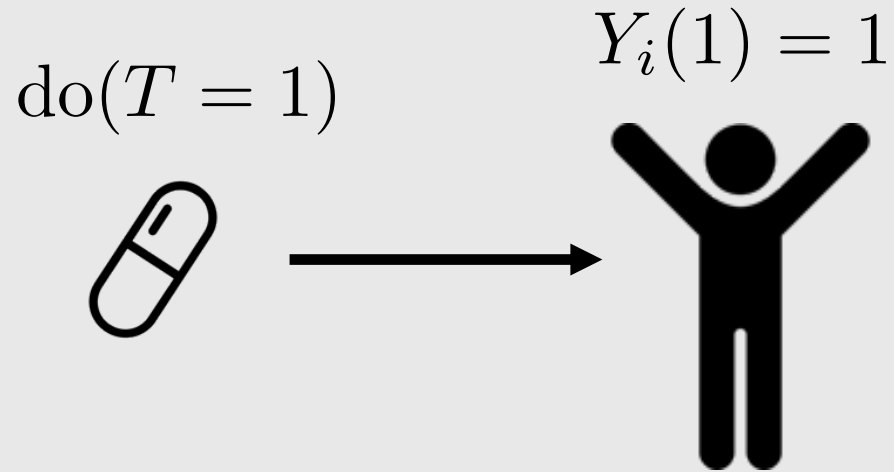


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$$Y_i(1) - Y_i(0)$$

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**Causal effect**

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

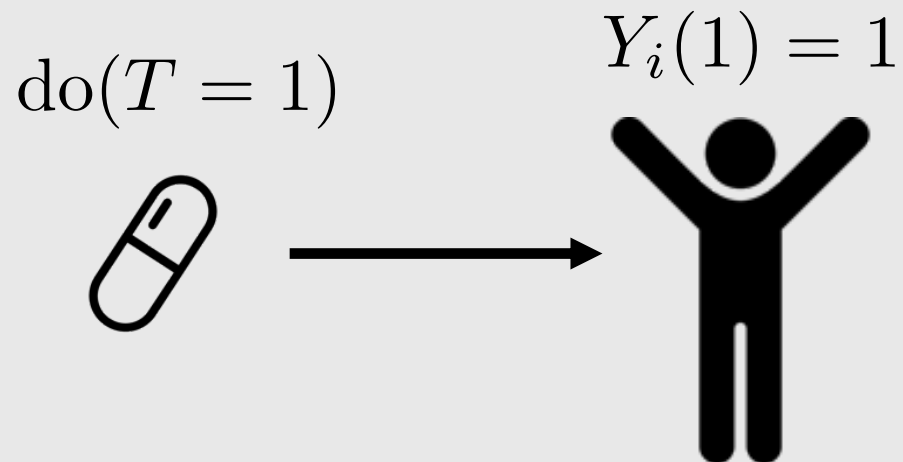
What are potential outcomes?

**The fundamental problem of causal inference**

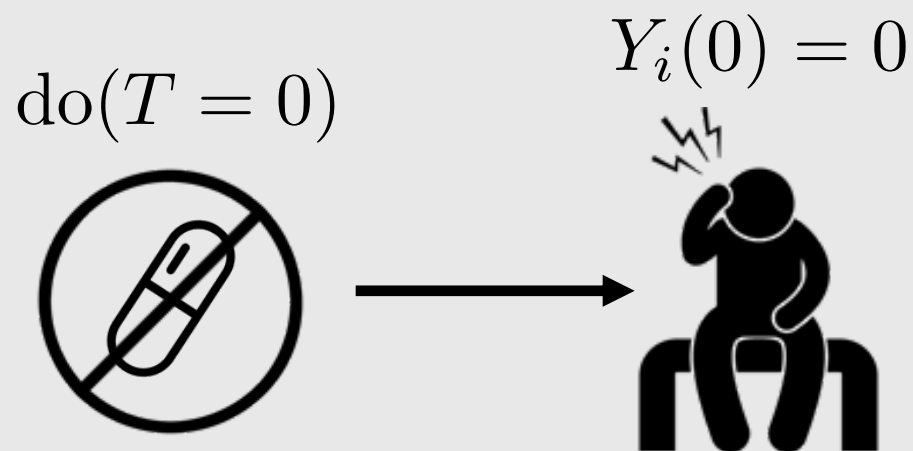
Getting around the fundamental problem of causal inference

A complete example with estimation

# Fundamental problem of causal inference



$T$  : observed treatment  
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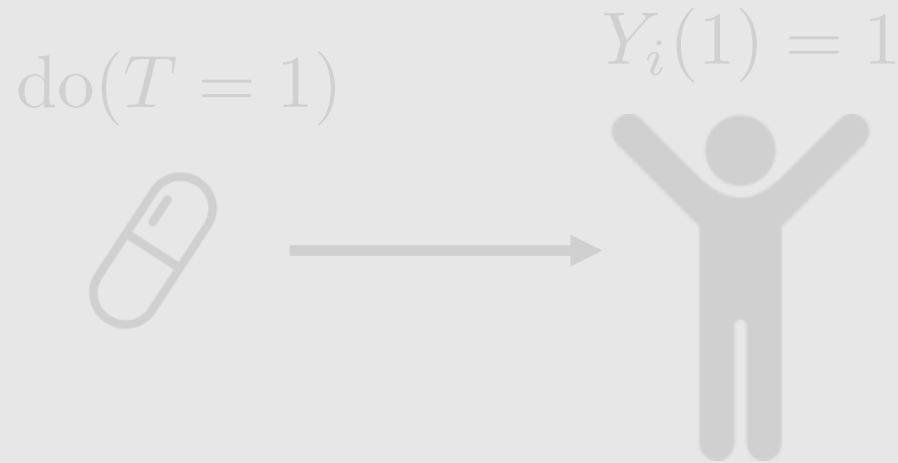


**Causal effect**

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

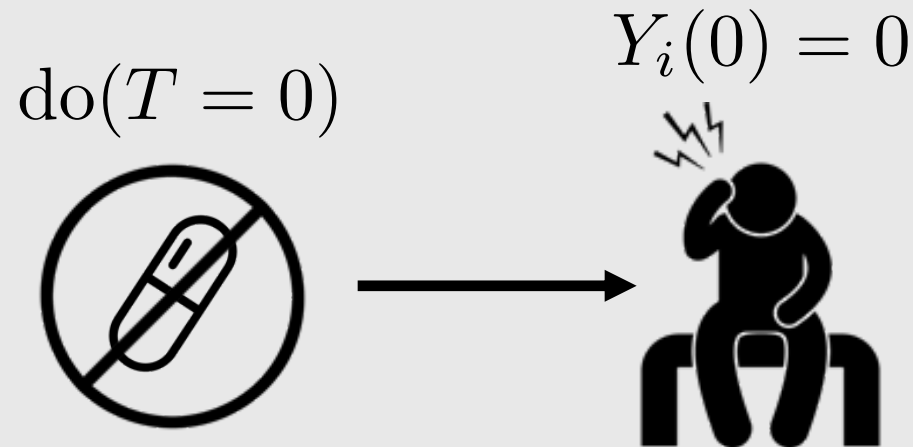
# Fundamental problem of causal inference

Counterfactual



$T$  : observed treatment  
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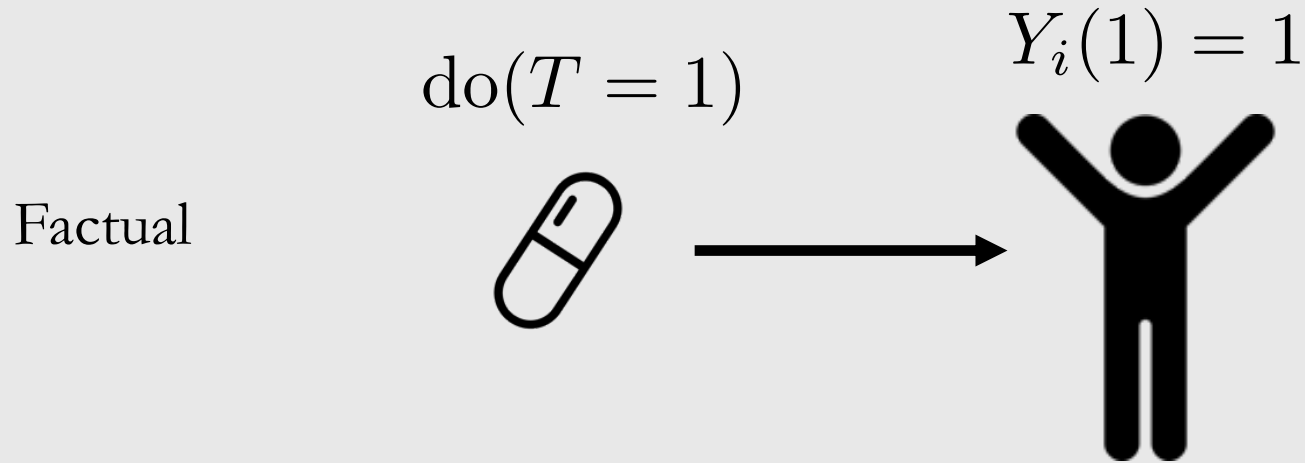
Factual



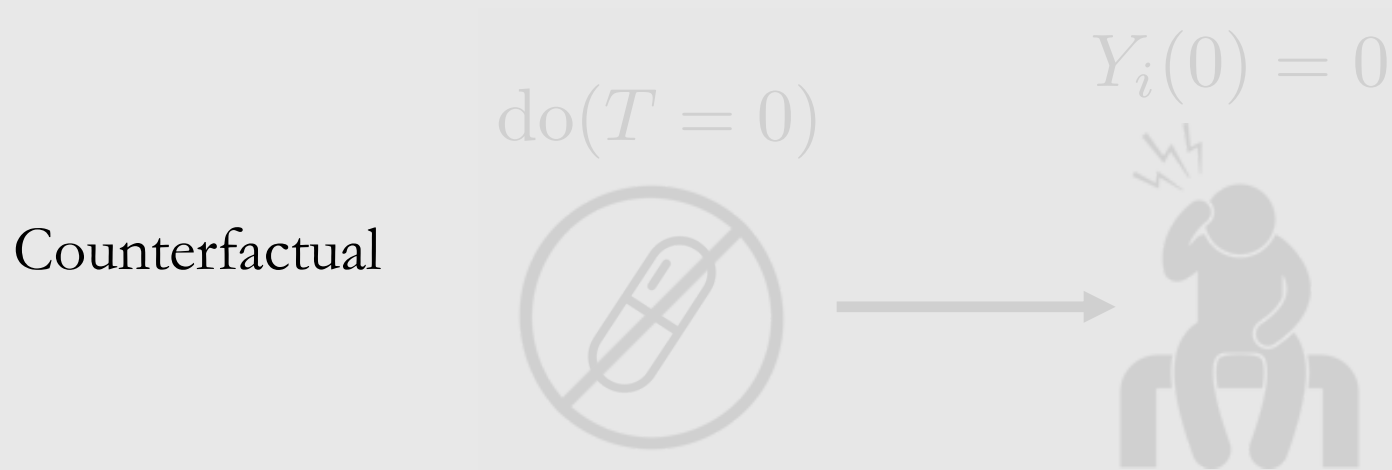
**Causal effect**

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

# Fundamental problem of causal inference



$T$  : observed treatment  
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 $Y_i(1)$  : potential outcome under treatment  
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## Causal effect

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



# Missing data interpretation

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	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

Question:

What is the fundamental problem of causal inference?

What are potential outcomes?

The fundamental problem of causal inference

**Getting around the fundamental problem of causal inference**

A complete example with estimation

# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	1	1	?	?

$T$  : observed treatment

$Y$  : observed outcome

$i$  : used in subscript to denote a  
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$Y_i(1)$  : potential outcome under treatment

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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	1	1	?	?

$T$  : observed treatment

$Y$  : observed outcome

$i$  : used in subscript to denote a  
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$Y_i(1)$  : potential outcome under treatment

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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	1	1	?	?

$T$  : observed treatment

$Y$  : observed outcome

$i$  : used in subscript to denote a  
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$Y_i(1)$  : potential outcome under treatment

$Y_i(0)$  : potential outcome under no treatment

# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	1	1	?	?

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

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	1	1	?	?

$T$  : observed treatment

$Y$  : observed outcome

$i$  : used in subscript to denote a  
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$Y_i(1)$  : potential outcome under treatment

$Y_i(0)$  : potential outcome under no treatment



# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

$T$  : observed treatment  
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 $i$  : used in subscript to denote a specific unit/individual  
 $Y_i(1)$  : potential outcome under treatment  
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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

2/3

$T$  : observed treatment  
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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

2/3

1/3

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$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

$$\underline{2/3} - \underline{1/3} = 1/3$$

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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

$$2/3 - 1/3 = 1/3$$

$T$  : observed treatment

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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

$$2/3 - 1/3 = 1/3$$

$T$  : observed treatment  
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# Average treatment effect (ATE)

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

$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

associational difference

$T$  : observed treatment

$Y$  : observed outcome

$i$  : used in subscript to denote a specific unit/individual

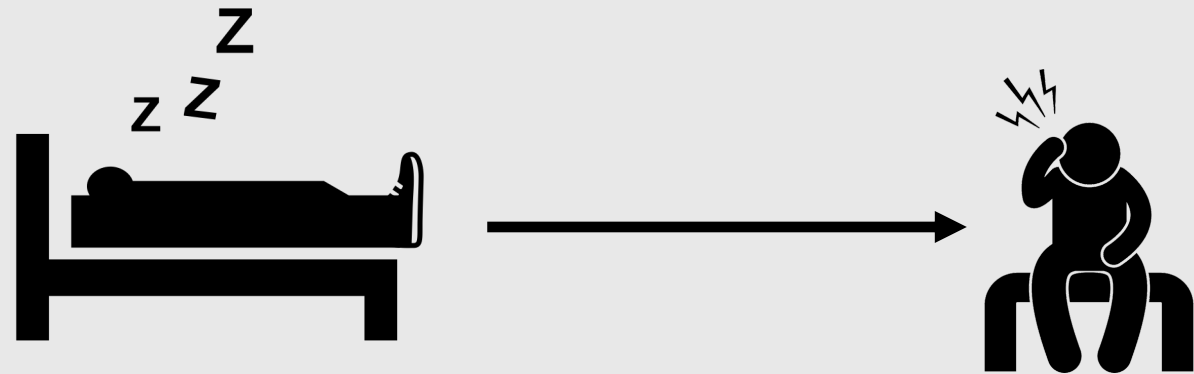
$Y_i(1)$  : potential outcome under treatment

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$$2/3 - 1/3 = 1/3$$

# Association is not causation

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

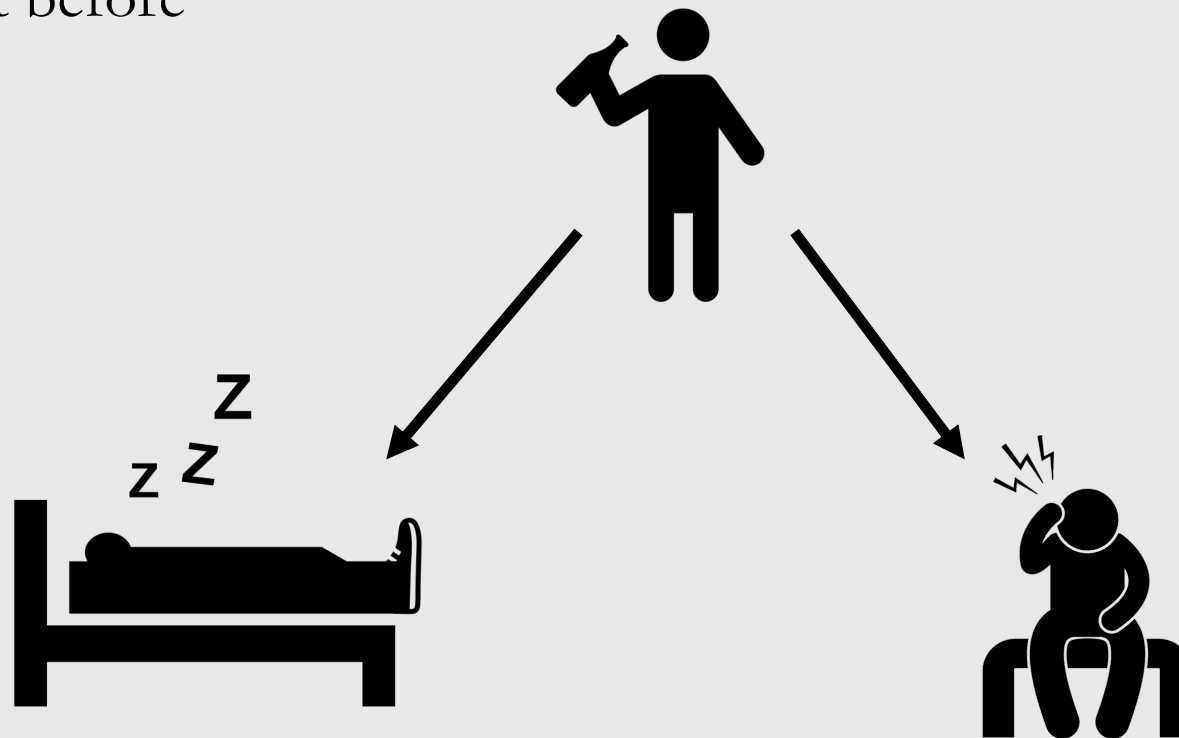




# Association is not causation

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

Common cause: drinking the night before

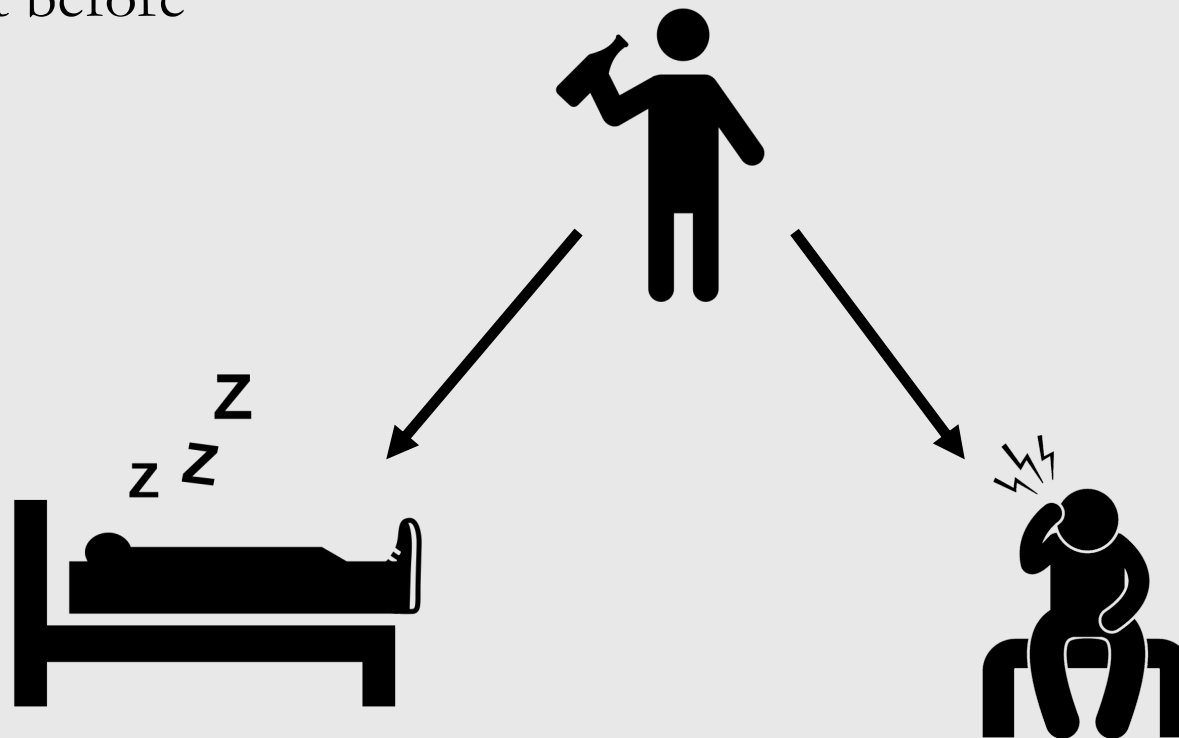


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Common cause: drinking the night before

1. Confounding

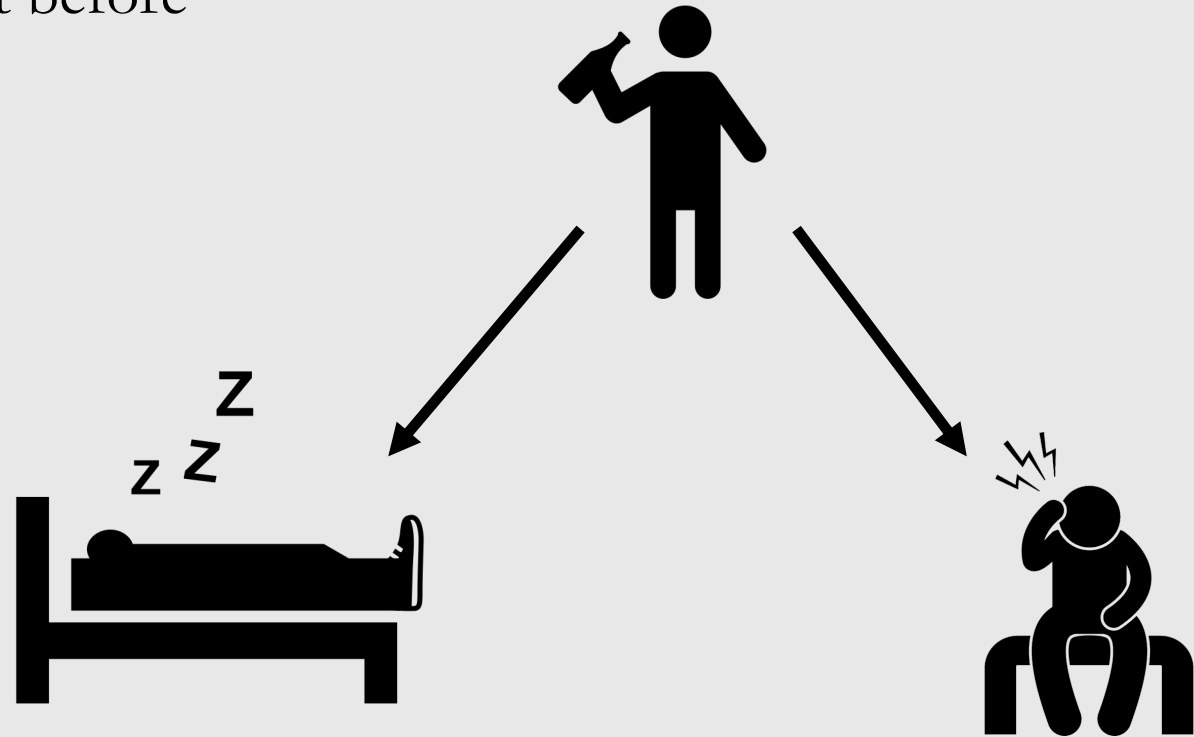
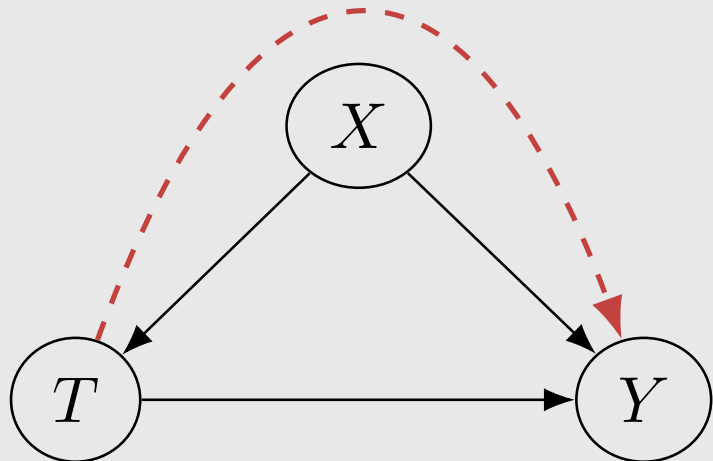


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## 1. Confounding

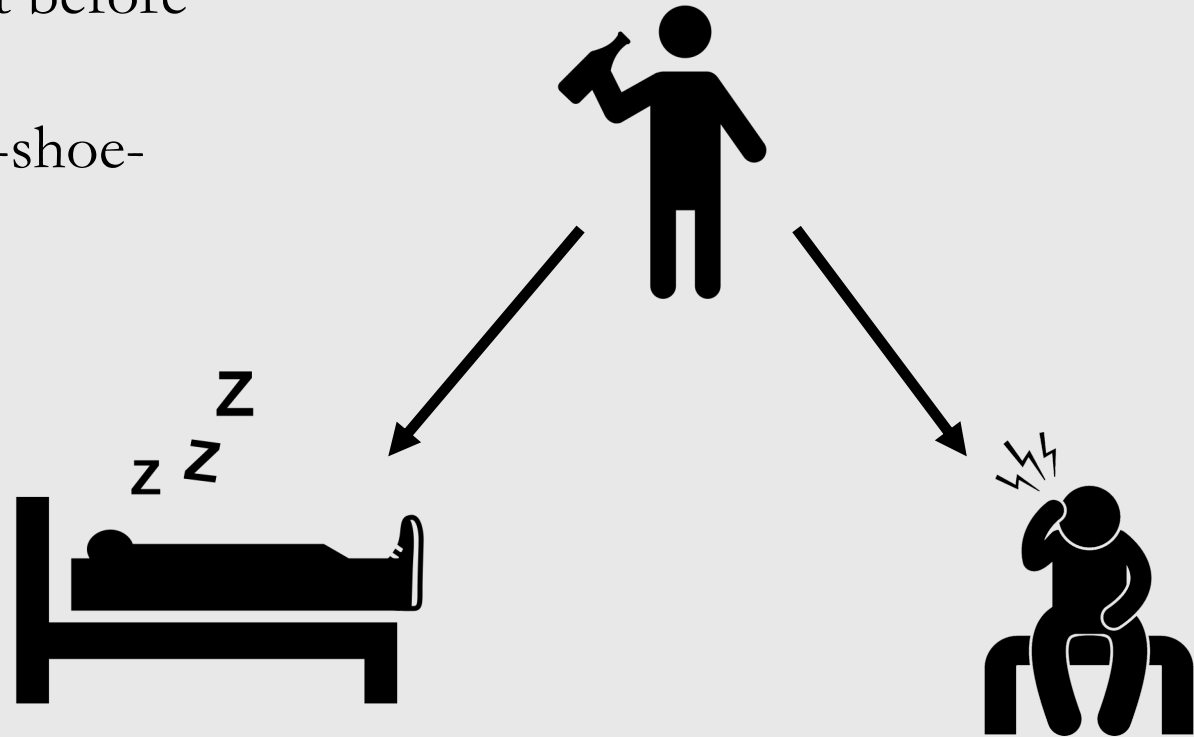
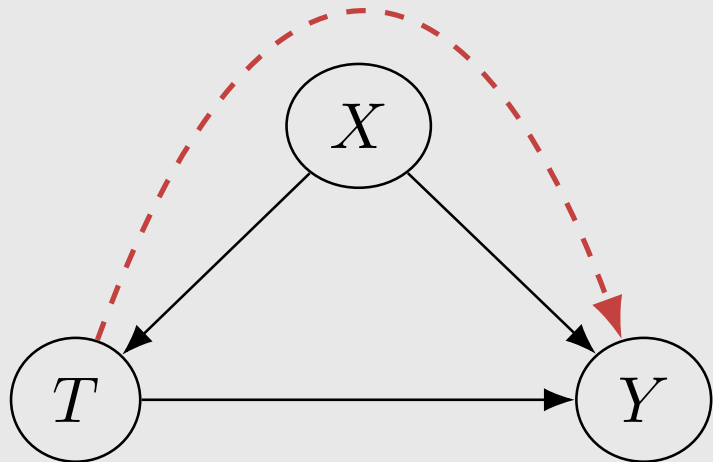


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Sleeping with shoes on is strongly correlated with waking up with a headache

Common cause: drinking the night before

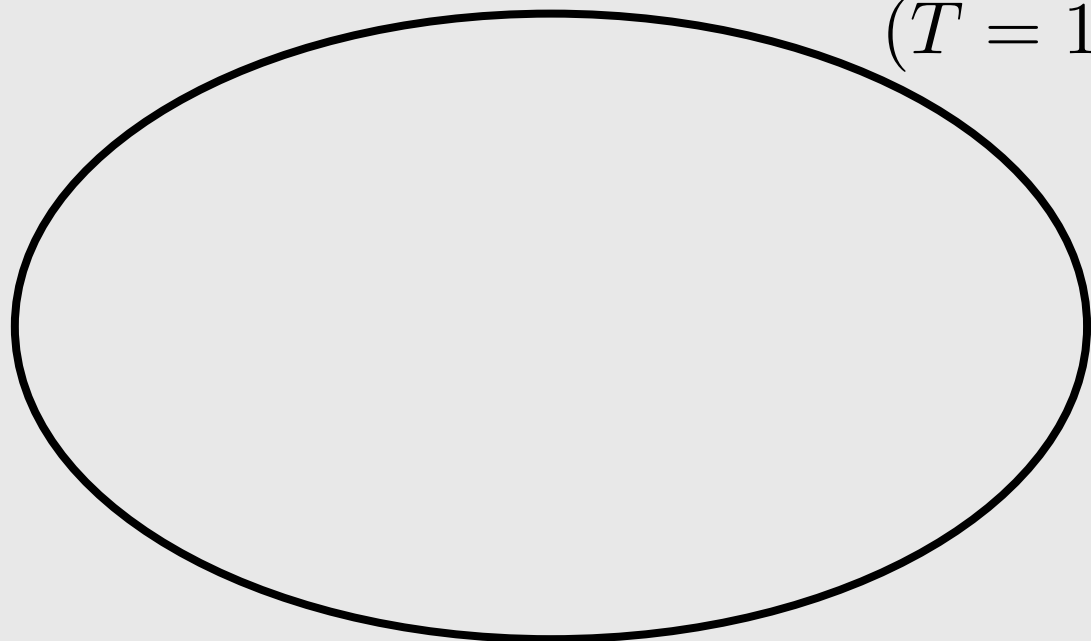
1. **Confounding**
2. Shoe-sleepers differ from non-shoe-sleepers in a key way



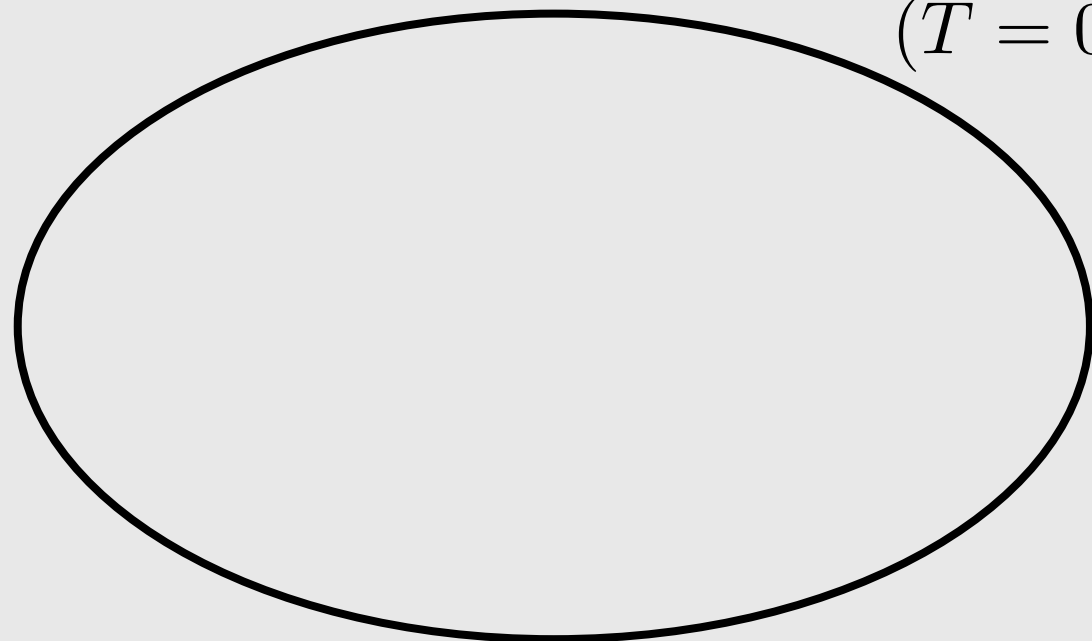
Why? Because the groups are not comparable

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

Went to sleep **with shoes** on  
( $T = 1$ )



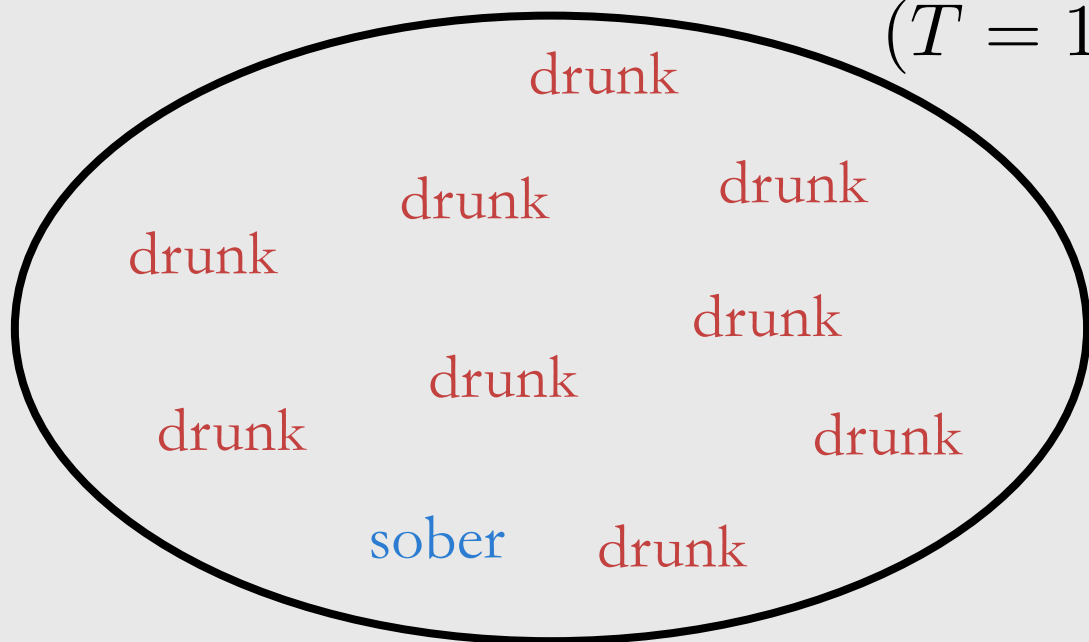
Went to sleep **without shoes** on  
( $T = 0$ )



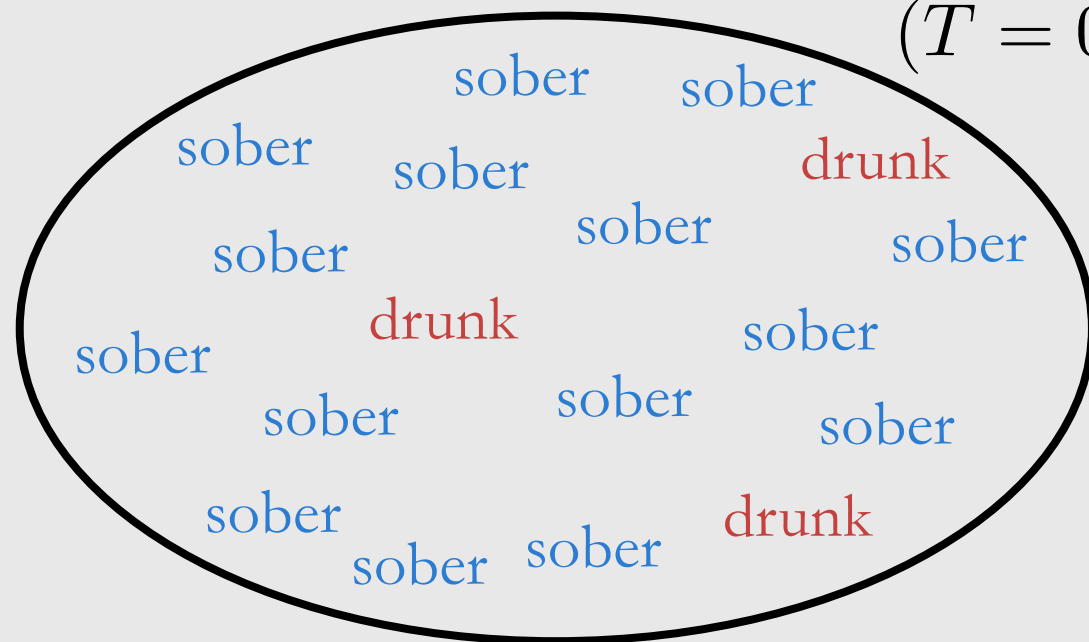
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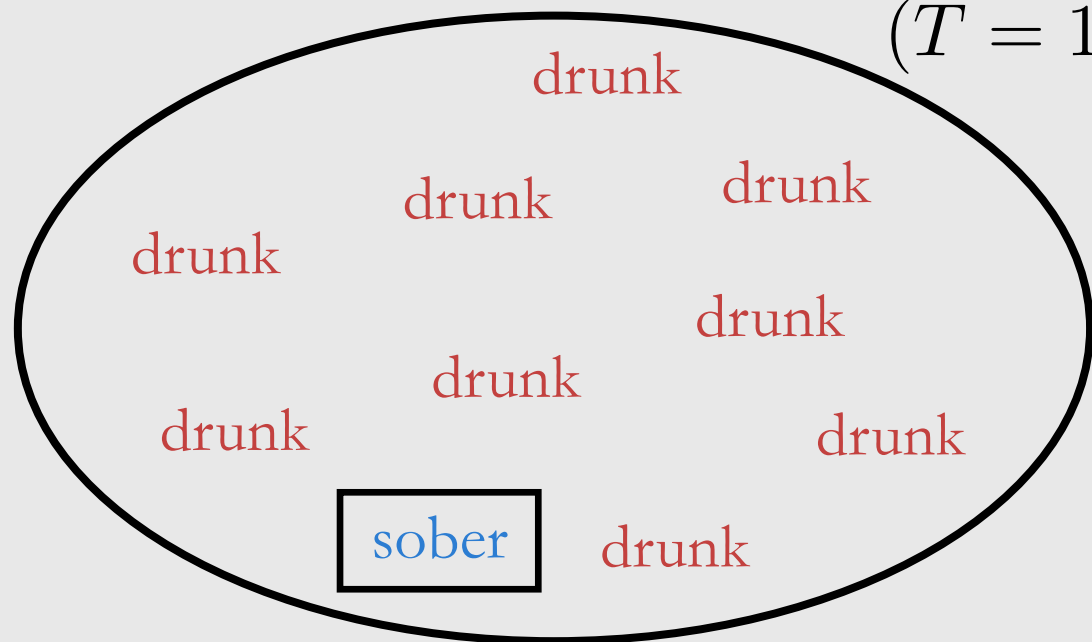
Went to sleep **without shoes** on  
( $T = 0$ )



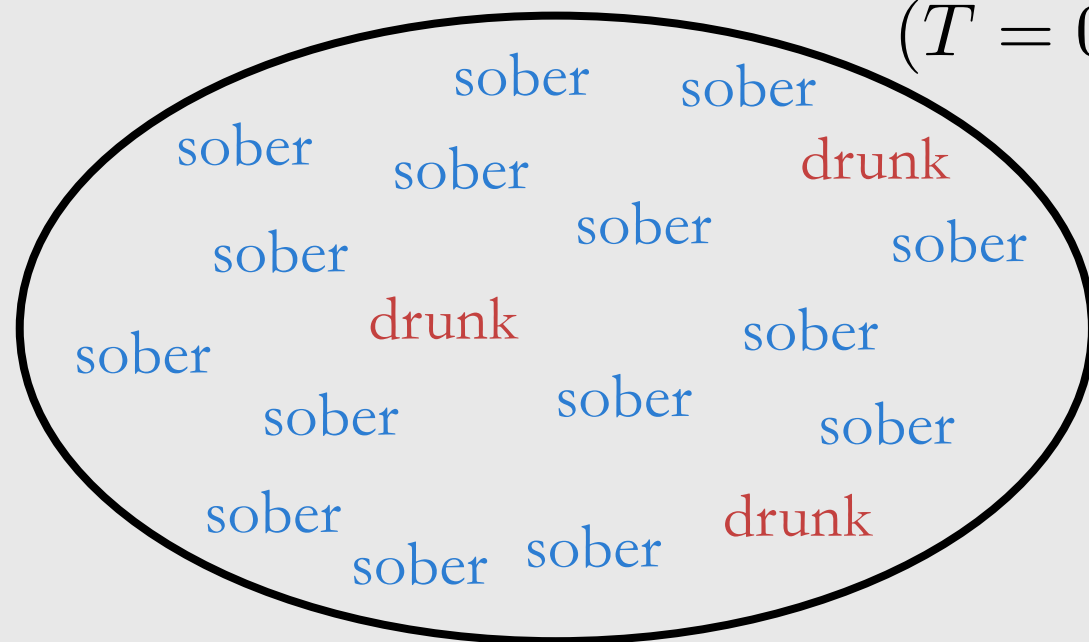
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Went to sleep **with shoes** on  
( $T = 1$ )



Went to sleep **without shoes** on  
( $T = 0$ )



# Why? Because the groups are not comparable

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

Went to sleep **with shoes** on  
( $T = 1$ )

Went to sleep **without shoes** on  
( $T = 0$ )

drunk

drunk

r/unpopularopinion



Posted by u/jimmythang34 1 year ago

2.1k



sleeping with shoes on is comfortable

sober

drunk

sober

sober

sober

drunk

sober

sober

sober

sober

sober

drunk

sober

sober

sober

sober

sober

sober

sober

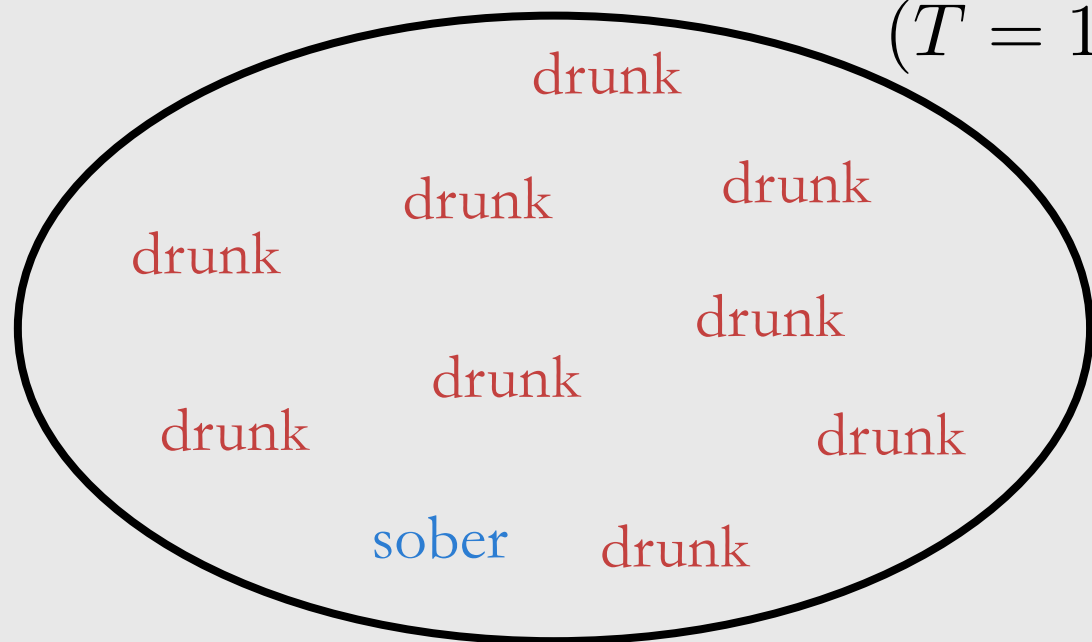
drunk



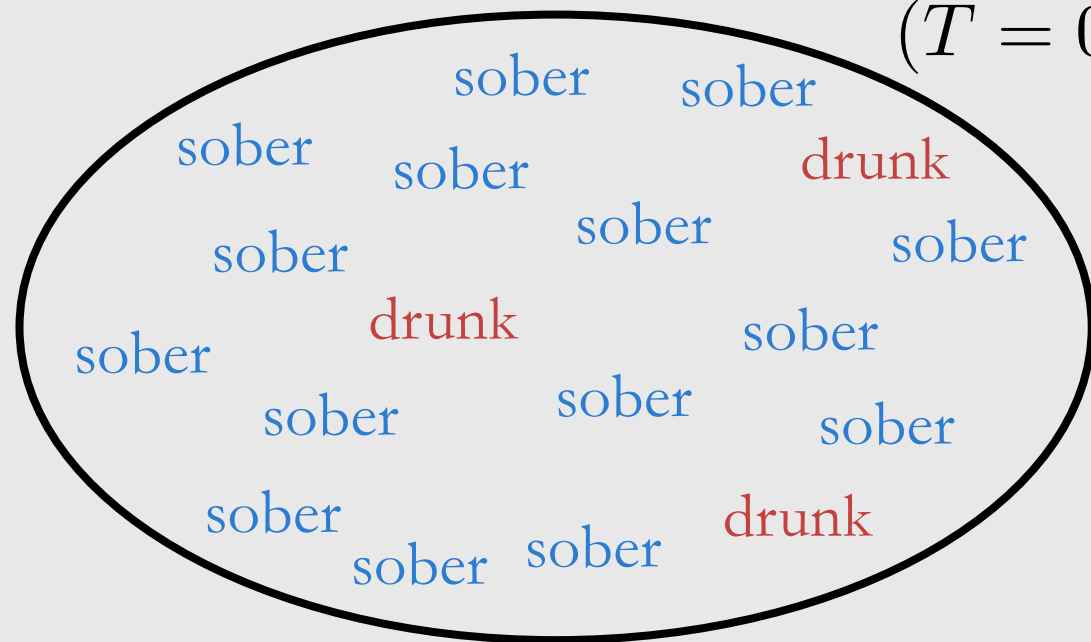
# What would comparable groups look like?

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

Went to sleep **with shoes** on  
( $T = 1$ )



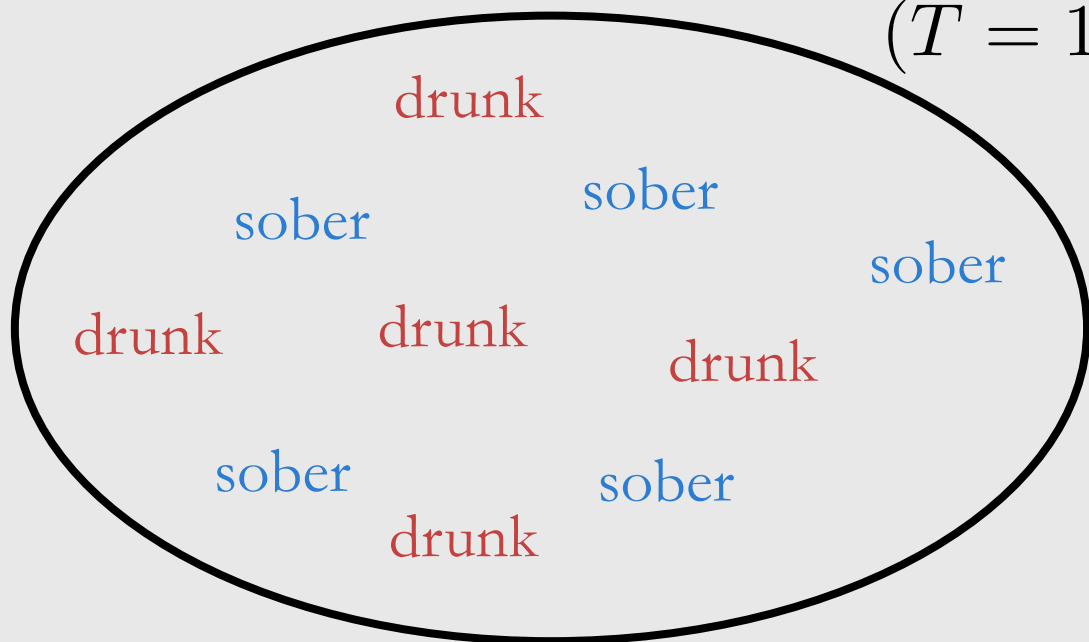
Went to sleep **without shoes** on  
( $T = 0$ )



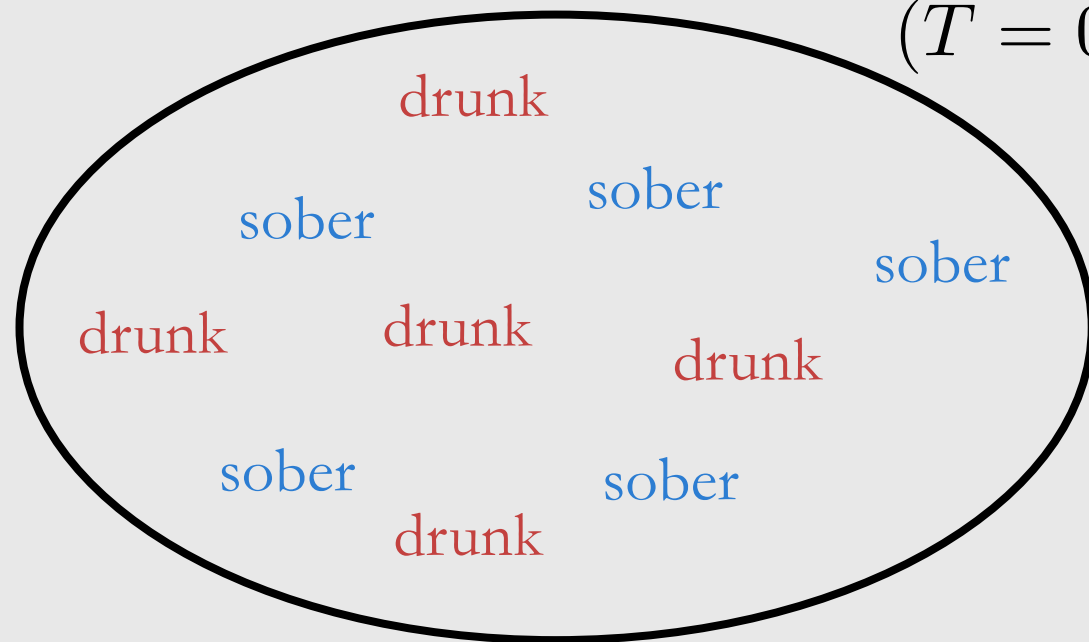
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Went to sleep **with shoes** on  
( $T = 1$ )



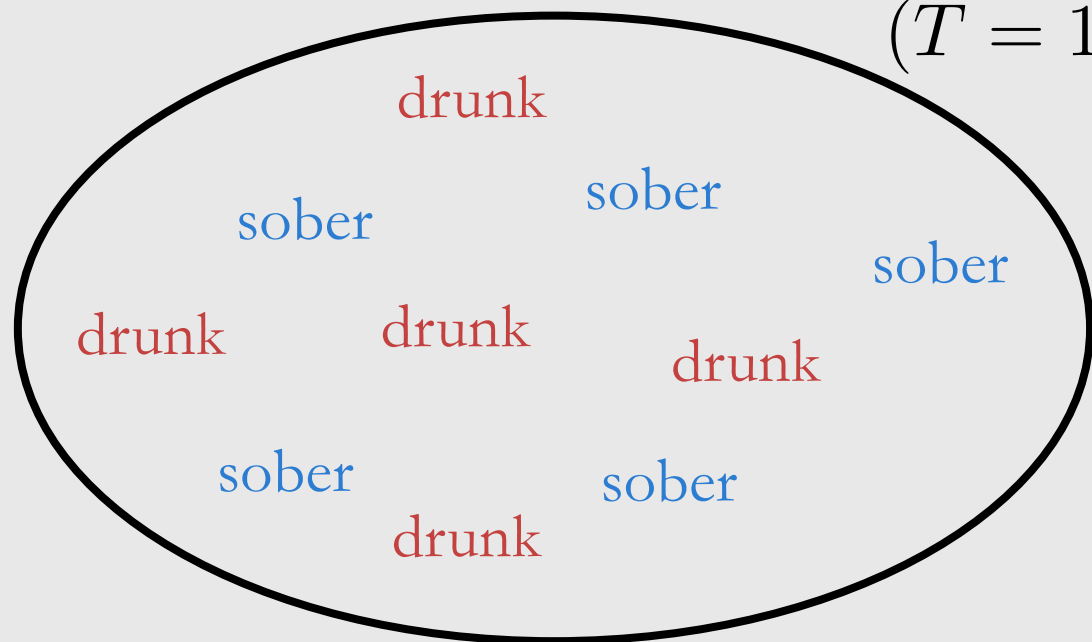
Went to sleep **without shoes** on  
( $T = 0$ )



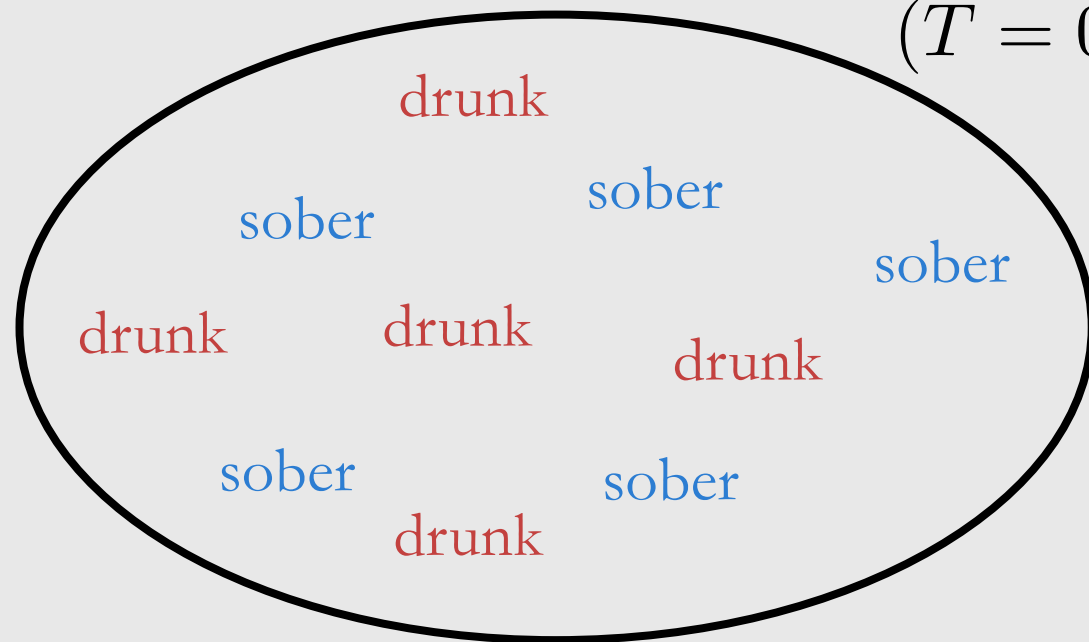
# What would comparable groups look like?

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

Went to sleep **with shoes** on  
( $T = 1$ )



Went to sleep **without shoes** on  
( $T = 0$ )



Question:

Why is association not causation?

What assumptions would make  
the ATE equal to the  
associational difference?

Ignorability:  $(Y(1), Y(0)) \perp\!\!\!\perp T$

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$i$	$T$	$Y$	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0	?	0	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	1	1	?	?

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$$\begin{aligned}\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] &= \mathbb{E}[Y(1) \mid T = 1] - \mathbb{E}[Y(0) \mid T = 0] \quad (\text{ignorability}) \\ &= \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0]\end{aligned}$$

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2/3

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2/3
1/3

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$$\frac{2}{3} - \frac{1}{3} = \frac{1}{3}$$

Ignorability:  $(Y(1), Y(0)) \perp\!\!\!\perp T$

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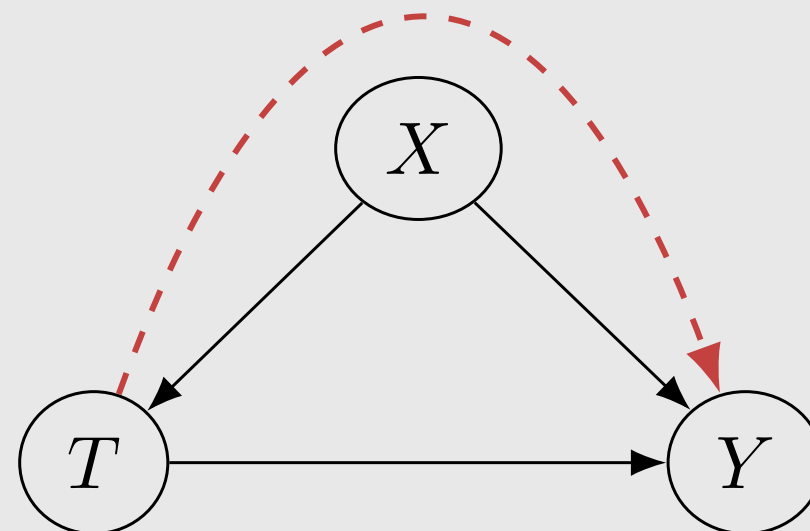
$$2/3 - 1/3 = 1/3$$

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$$2/3 - 1/3 = 1/3$$

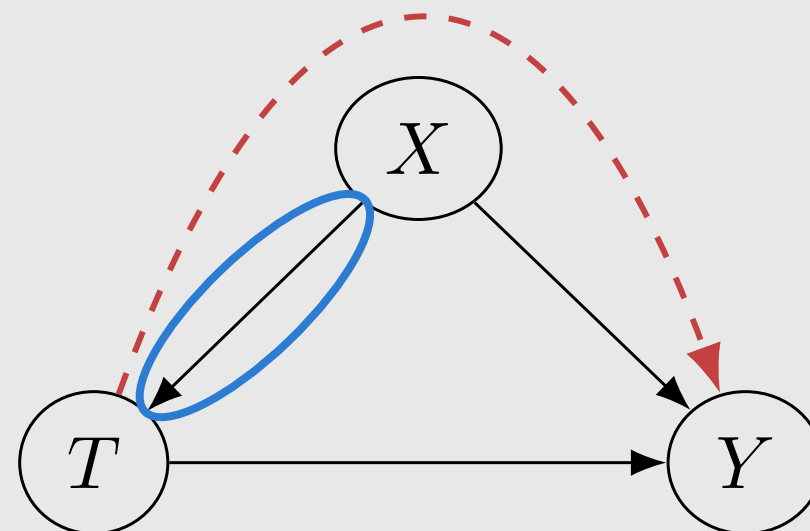


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$$2/3 - 1/3 = 1/3$$



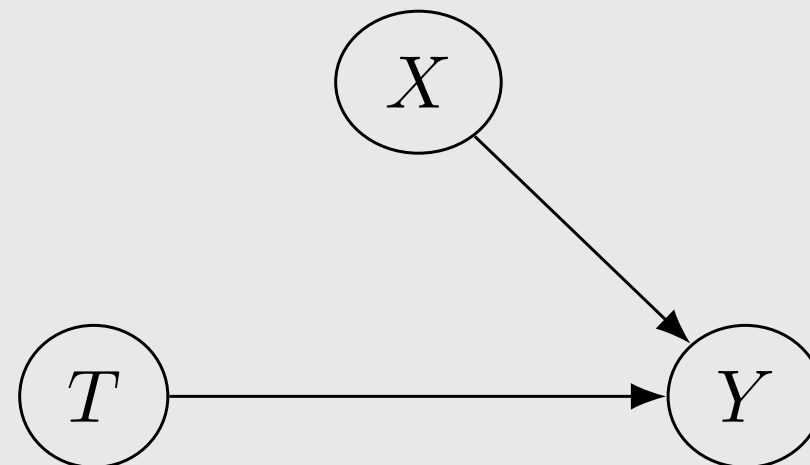


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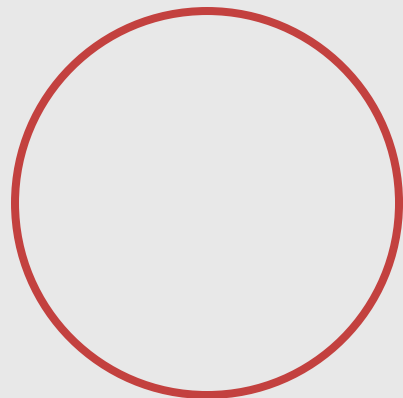
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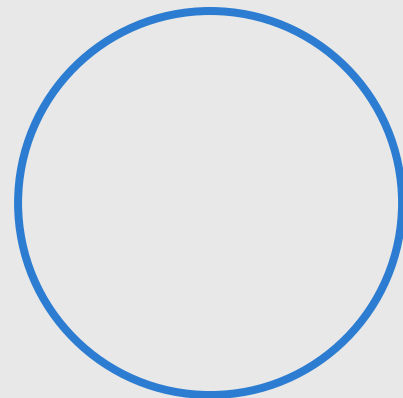
# Another perspective: exchangeability

$T = 1$



$$\mathbb{E}[Y \mid T = 1] = y_1$$

$T = 0$



$$\mathbb{E}[Y \mid T = 0] = y_0$$

# Another perspective: exchangeability

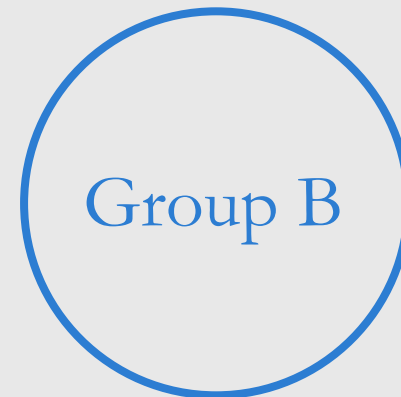
$T = 1$



Group A

$$\mathbb{E}[Y \mid T = 1] = y_1$$

$T = 0$

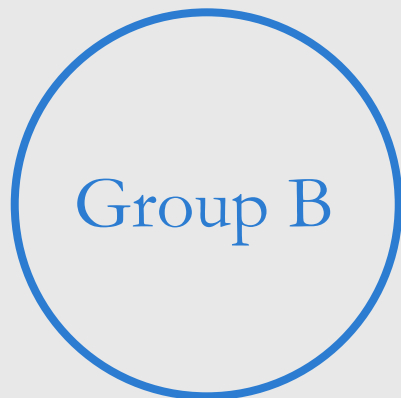


Group B

$$\mathbb{E}[Y \mid T = 0] = y_0$$

# Another perspective: exchangeability

$T = 1$



Group B

$$\mathbb{E}[Y \mid T = 1] = y_1$$

$T = 0$

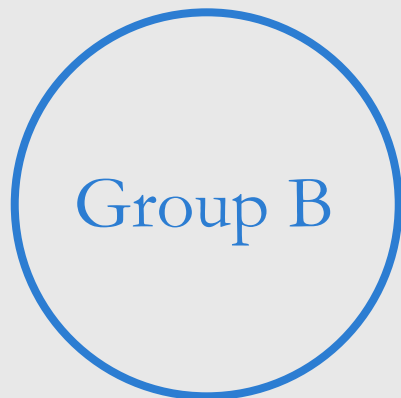


Group A

$$\mathbb{E}[Y \mid T = 0] = y_0$$

# Another perspective: exchangeability

$T = 1$



Group B

$$\underline{\mathbb{E}[Y \mid T = 1] = y_1}$$

$T = 0$



Group A

$$\underline{\mathbb{E}[Y \mid T = 0] = y_0}$$

# Another perspective: exchangeability

$T = 1$



Group B

$$\underline{\mathbb{E}[Y \mid T = 1] = y_1}$$

$T = 0$



Group A

$$\underline{\mathbb{E}[Y \mid T = 0] = y_0}$$

Before switch

After switch

$$\mathbb{E}[Y(1) \mid T = 1] \underline{=} \mathbb{E}[Y(1) \mid T = 0]$$

# Another perspective: exchangeability

$T = 1$



Group B

$$\underline{\mathbb{E}[Y \mid T = 1] = y_1}$$

$T = 0$



Group A

$$\underline{\mathbb{E}[Y \mid T = 0] = y_0}$$

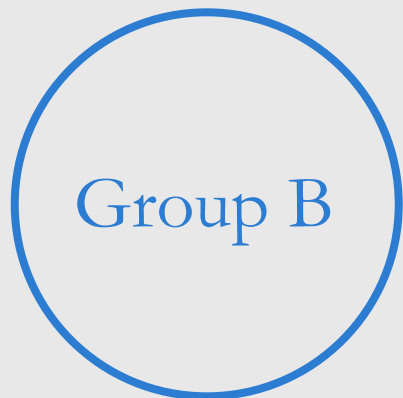
Before switch

After switch

$$\mathbb{E}[Y(1) \mid T = 1] \underline{=} \mathbb{E}[Y(1) \mid T = 0] = \mathbb{E}[Y(1)]$$

# Another perspective: exchangeability

$T = 1$



Group B

$$\underline{\mathbb{E}[Y \mid T = 1] = y_1}$$

$T = 0$



Group A

$$\underline{\mathbb{E}[Y \mid T = 0] = y_0}$$

Before switch

After switch

$$\mathbb{E}[Y(1) \mid T = 1] \underline{=} \mathbb{E}[Y(1) \mid T = 0] = \mathbb{E}[Y(1)]$$

$$\mathbb{E}[Y(0) \mid T = 0] \underline{=} \mathbb{E}[Y(0) \mid T = 1] = \mathbb{E}[Y(0)]$$



## Aside: identifiability

$$\begin{aligned}\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] &= \mathbb{E}[Y(1) \mid T = 1] - \mathbb{E}[Y(0) \mid T = 0] \quad (\text{ignorability}) \\ &= \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0]\end{aligned}$$

## Aside: identifiability

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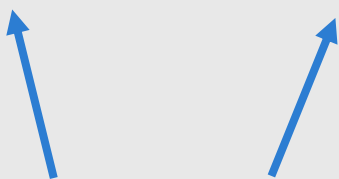
Causal quantities



# Aside: identifiability

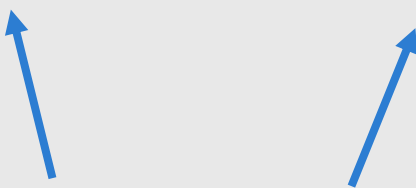
$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] = \mathbb{E}[Y(1) \mid T = 1] - \mathbb{E}[Y(0) \mid T = 0] \quad (\text{ignorability})$$

Causal quantities



$$= \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0]$$

Statistical quantities

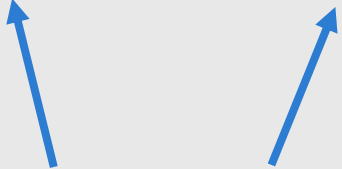


(accessible, since we have  $P(x, t, y)$ )

# Aside: identifiability

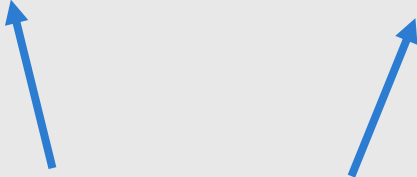
$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] = \mathbb{E}[Y(1) \mid T = 1] - \mathbb{E}[Y(0) \mid T = 0] \quad (\text{ignorability})$$

Causal quantities



$$= \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0]$$

Statistical quantities (accessible, since we have  $P(x, t, y)$ )



A causal quantity (e.g.  $\mathbb{E}[Y(t)]$ ) is **identifiable** if we can compute it from a purely statistical quantity (e.g.  $\mathbb{E}[Y \mid t]$ )

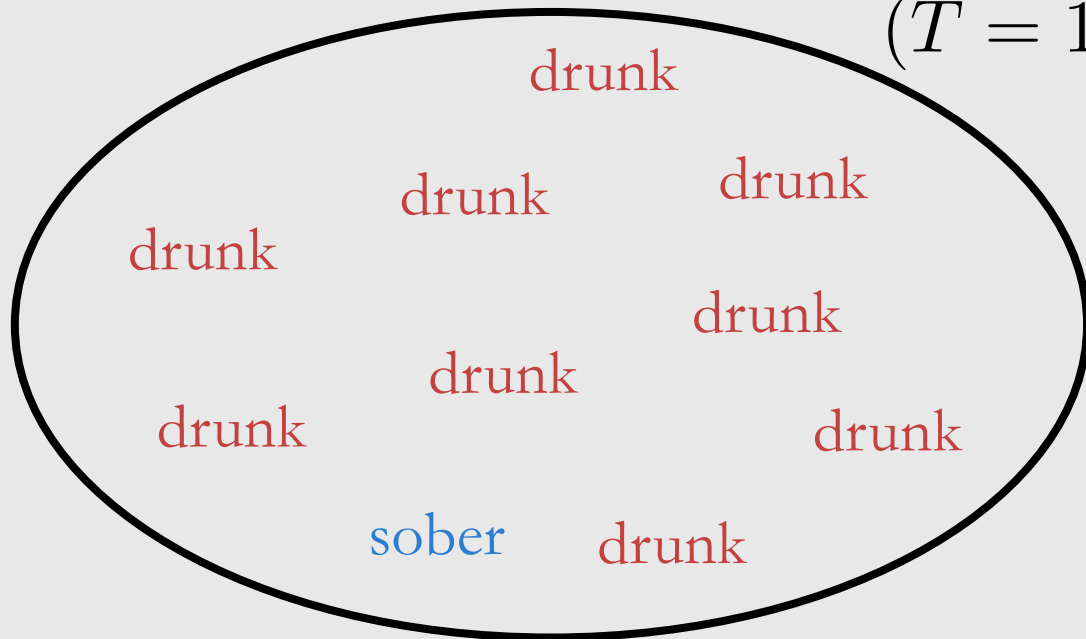
# Randomized control trial (RCT)



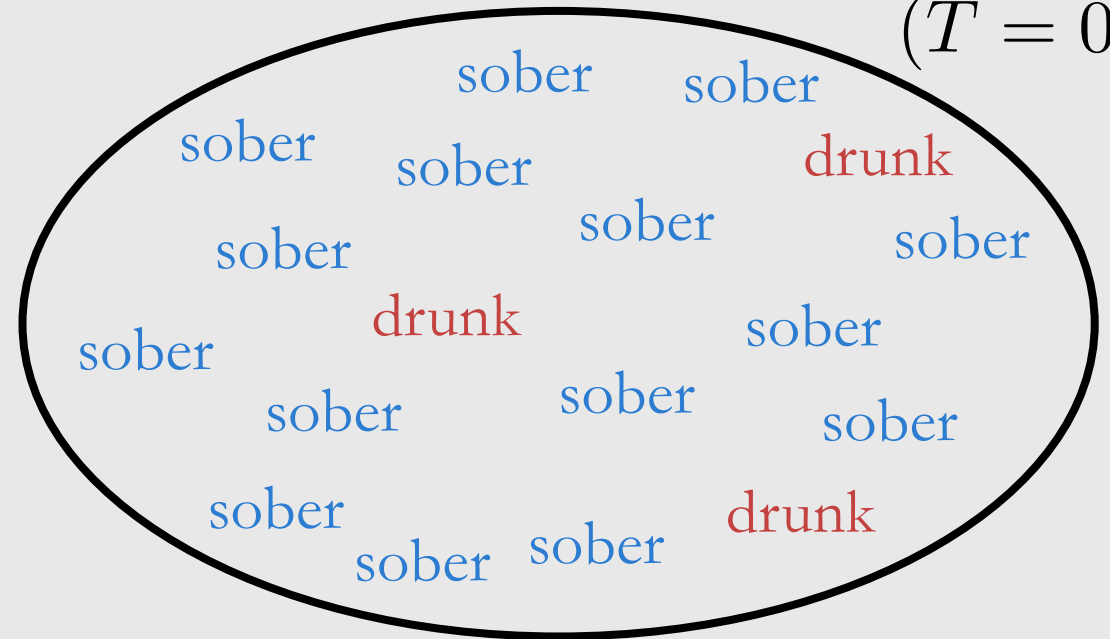
# Randomized control trial (RCT)



Went to sleep **with shoes** on  
( $T = 1$ )



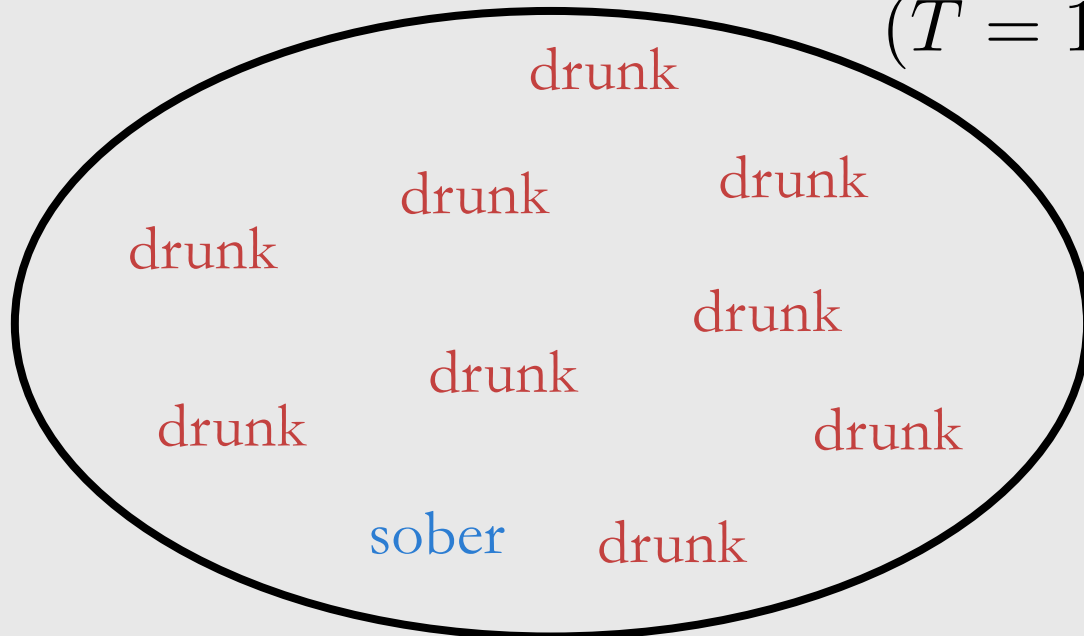
Went to sleep **without shoes** on  
( $T = 0$ )



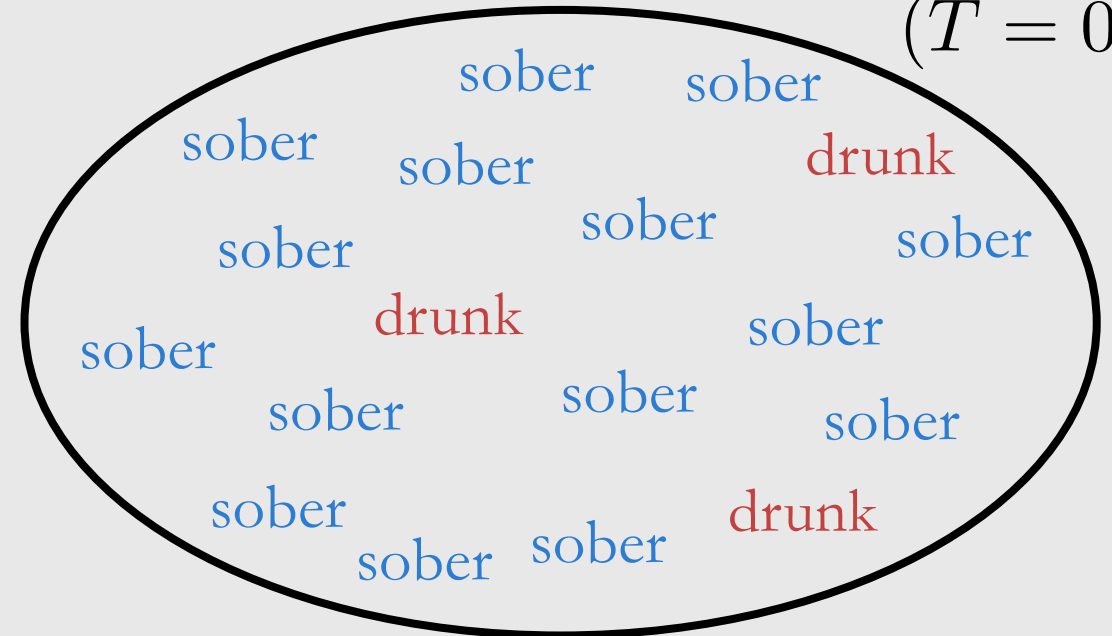
# Randomized control trial (RCT)



Slept **with shoes** on  
( $T = 1$ )



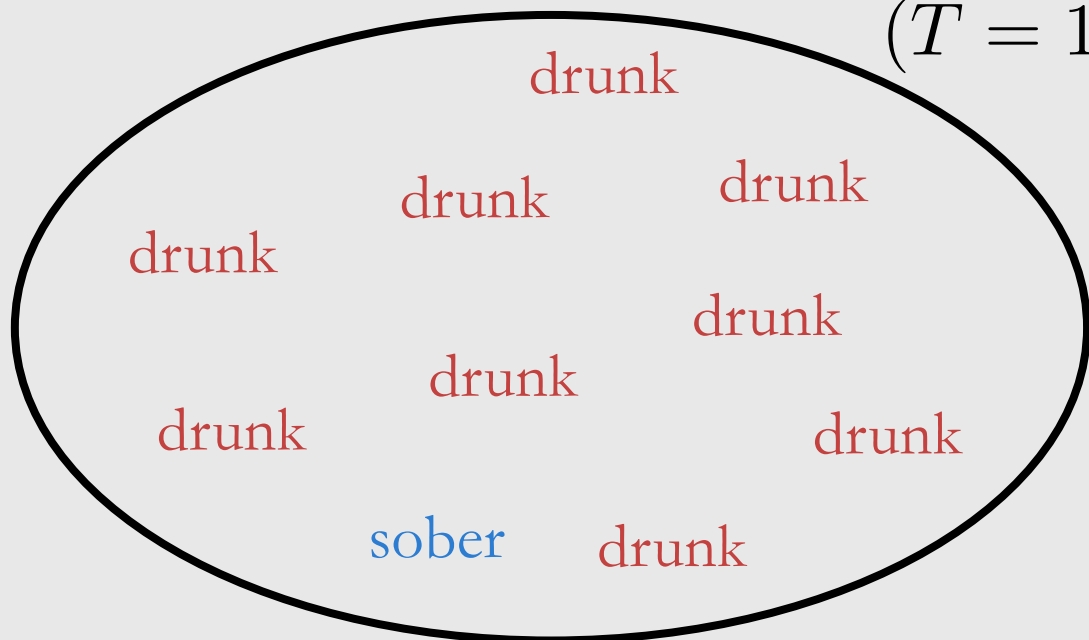
Went to sleep **without shoes** on  
( $T = 0$ )



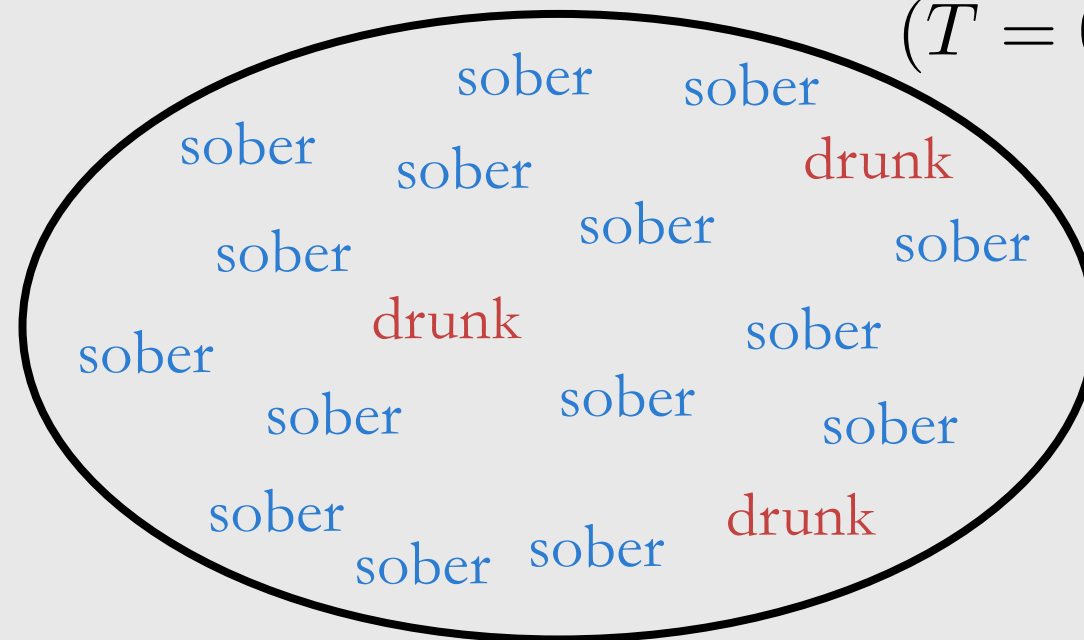
# Randomized control trial (RCT)



Slept **with shoes** on  
( $T = 1$ )



Slept **without shoes** on  
( $T = 0$ )

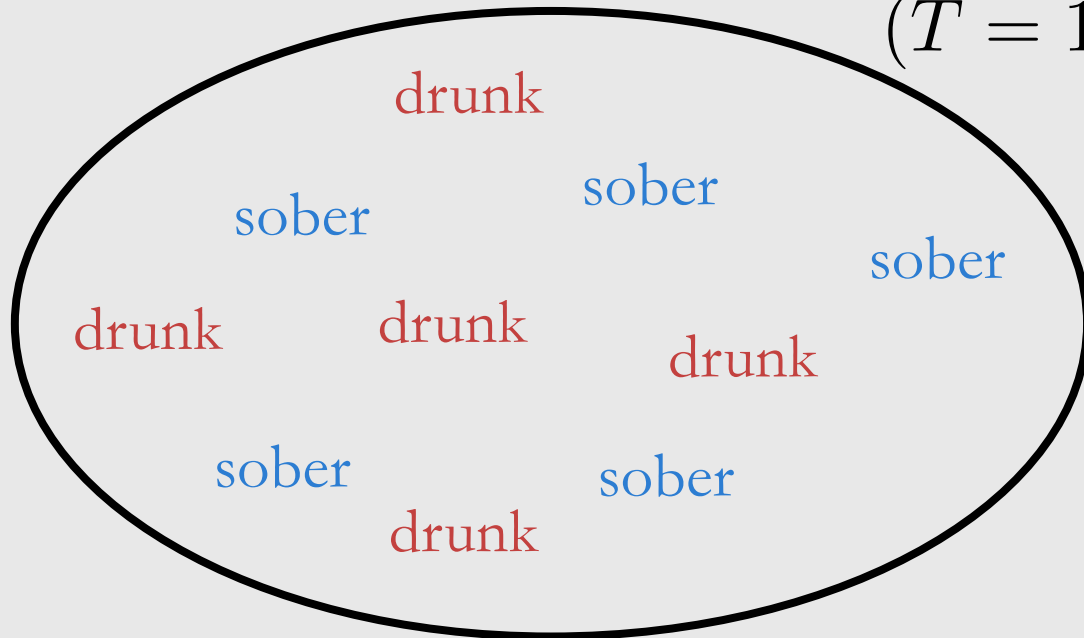




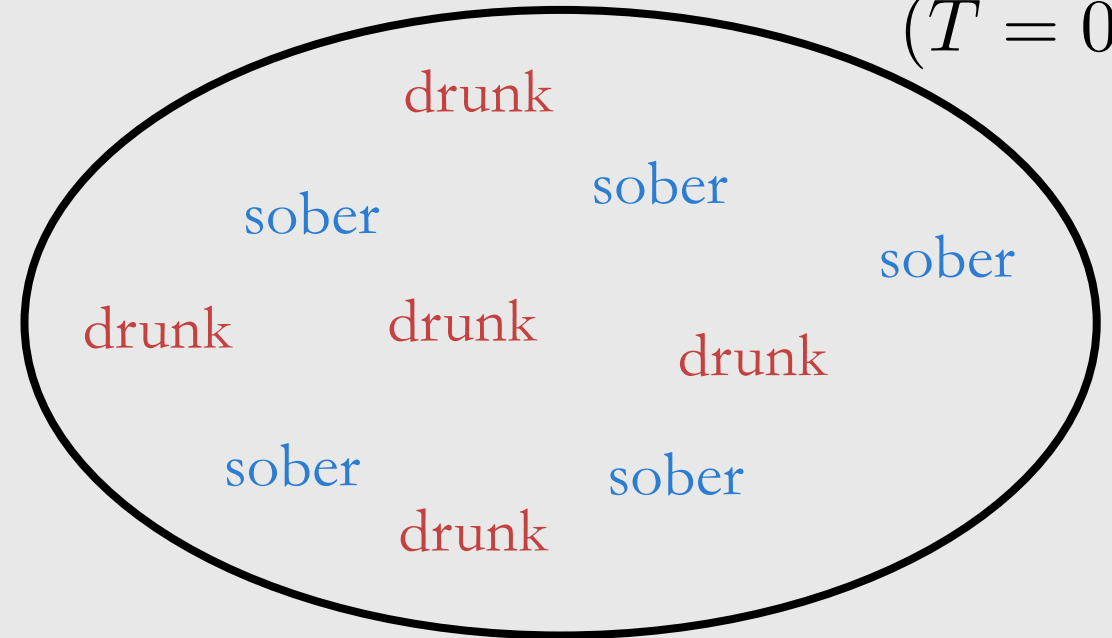
# Randomized control trial (RCT)



Slept **with shoes** on  
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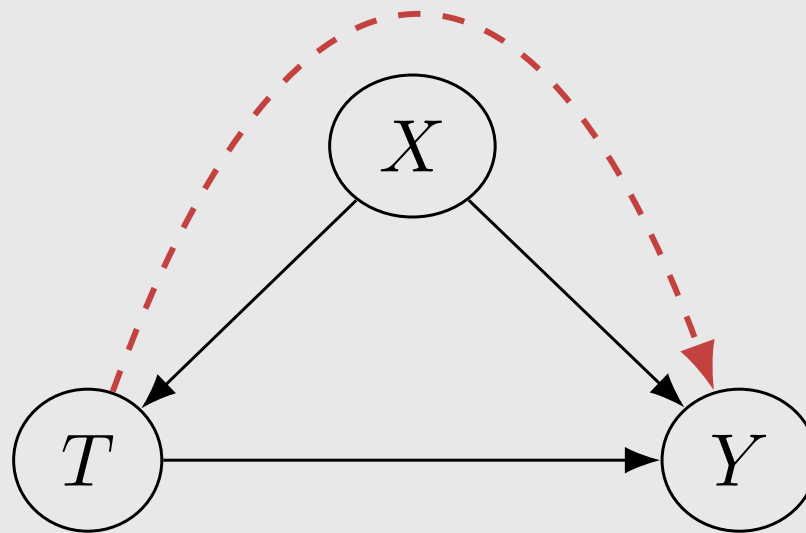


Slept **without shoes** on  
( $T = 0$ )

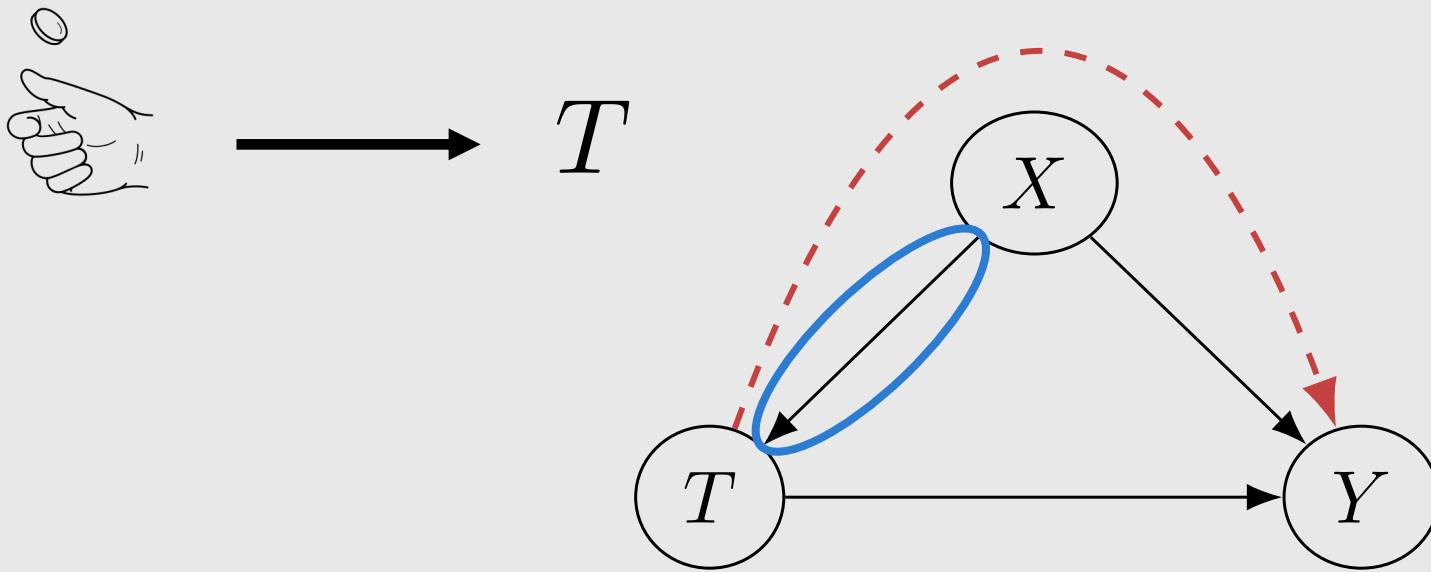


# Graphical interpretation of RCT

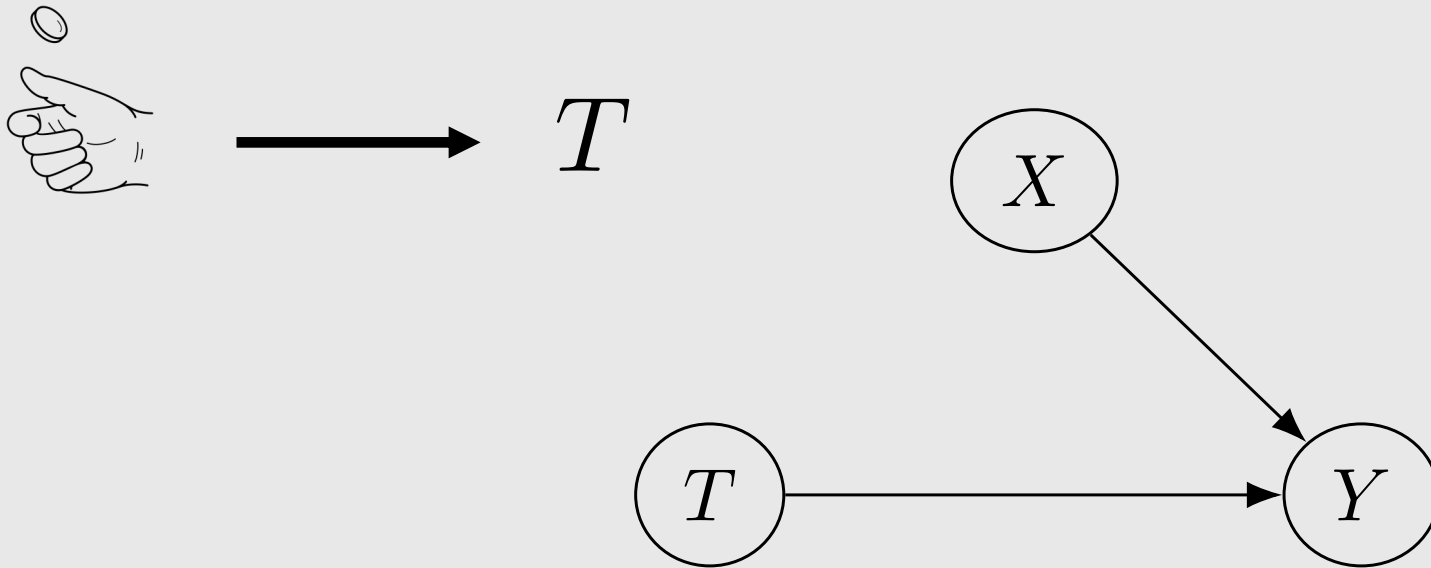
# Graphical interpretation of RCT



# Graphical interpretation of RCT



# Graphical interpretation of RCT



Question:

What important property does an RCT  
give us?

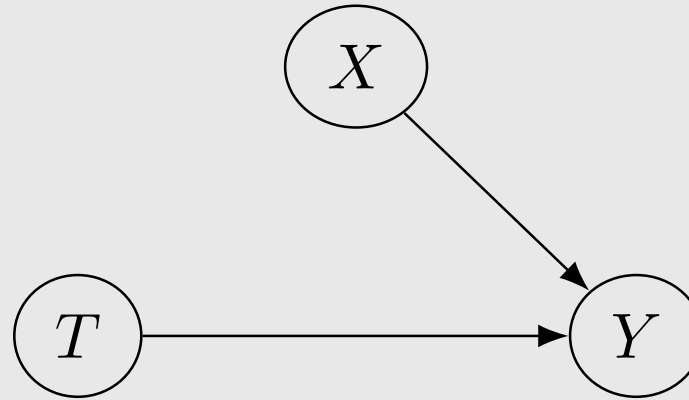
# Conditional exchangeability

Exchangeability:

$$(Y(1), Y(0)) \perp\!\!\!\perp T$$

# Conditional exchangeability

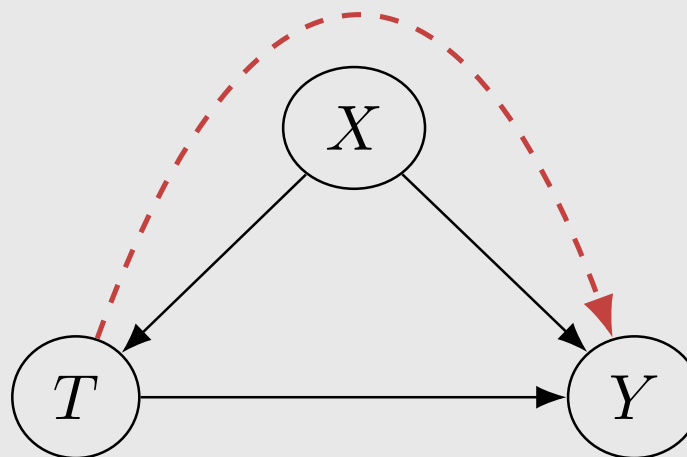
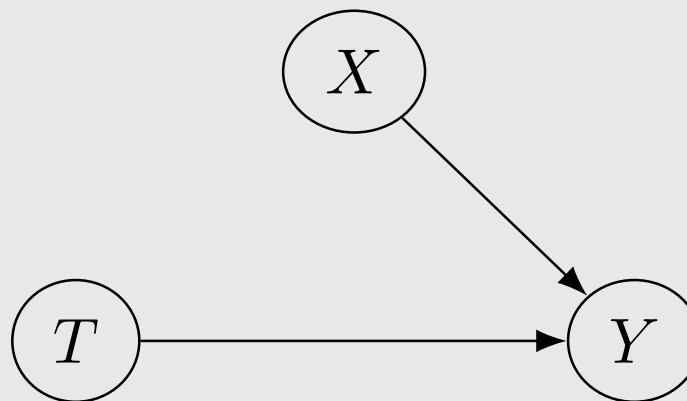
Exchangeability:  
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# Conditional exchangeability

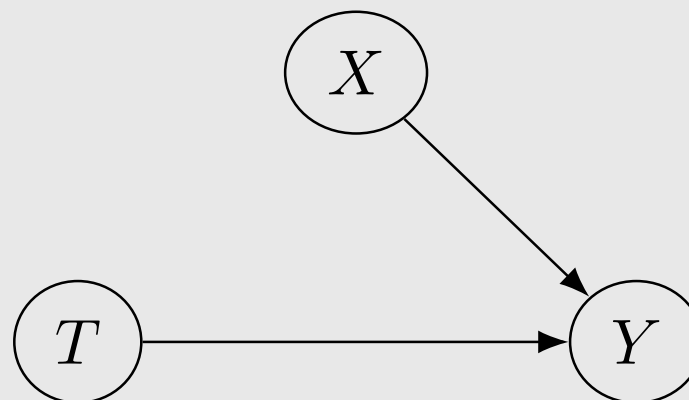
Exchangeability:  
 $(Y(1), Y(0)) \perp\!\!\!\perp T$



# Conditional exchangeability

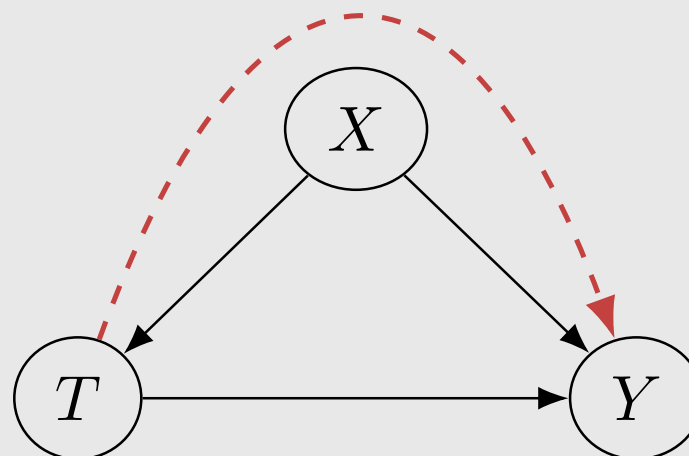
Exchangeability:

$$(Y(1), Y(0)) \perp\!\!\!\perp T$$



Conditional exchangeability:

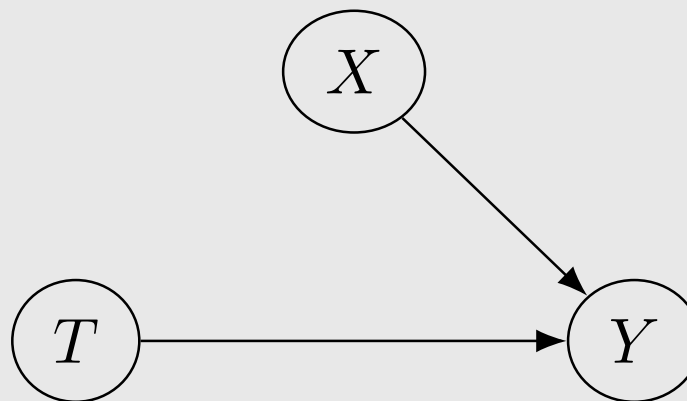
$$(Y(1), Y(0)) \perp\!\!\!\perp T \mid X$$



# Conditional exchangeability

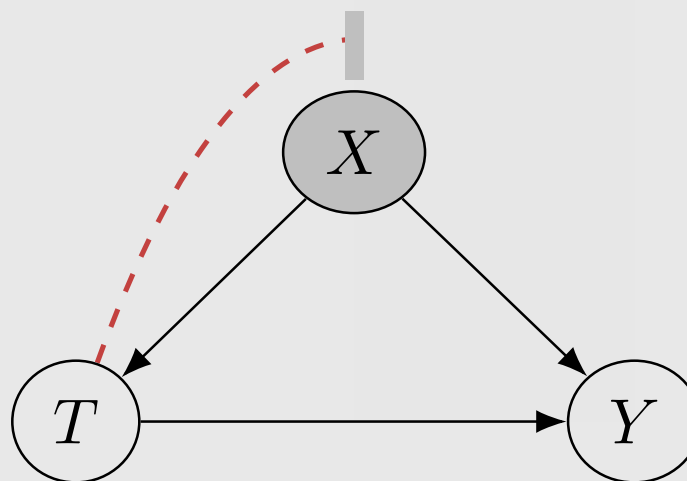
Exchangeability:

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# Identification of conditional average treatment effect

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What about the ATE?  $\mathbb{E}[Y(1) - Y(0)]$

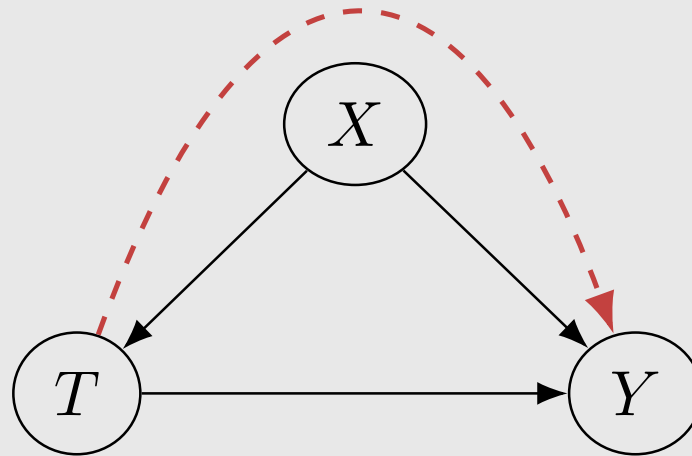


# The Adjustment Formula (identification of ATE)

$$\begin{aligned}\mathbb{E}[Y(1) - Y(0)] &= \mathbb{E}_X \mathbb{E}[Y(1) - Y(0) \mid X] \\ &= \mathbb{E}_X [\mathbb{E}[Y \mid T = 1, X] - \mathbb{E}[Y \mid T = 0, X]]\end{aligned}$$

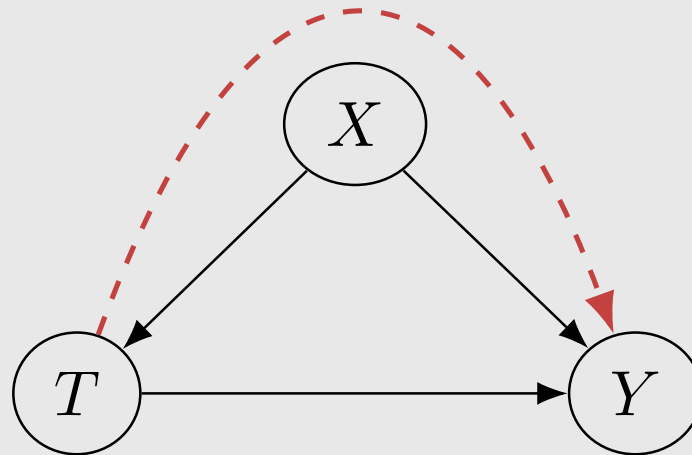
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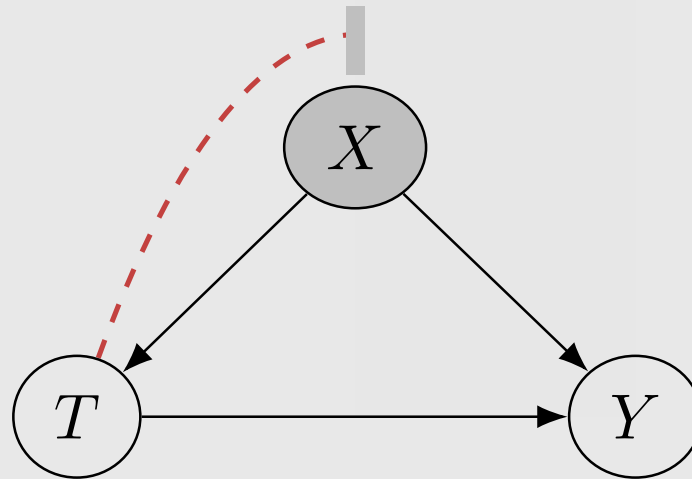
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# Unconfoundedness is an untestable assumption

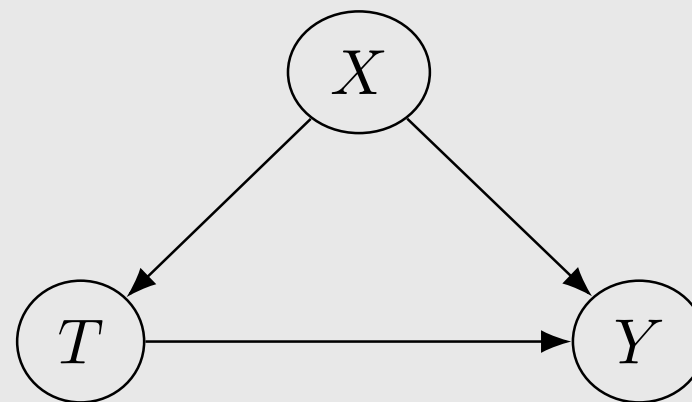
unconfoundedness = conditional ignorability = conditional exchangeability

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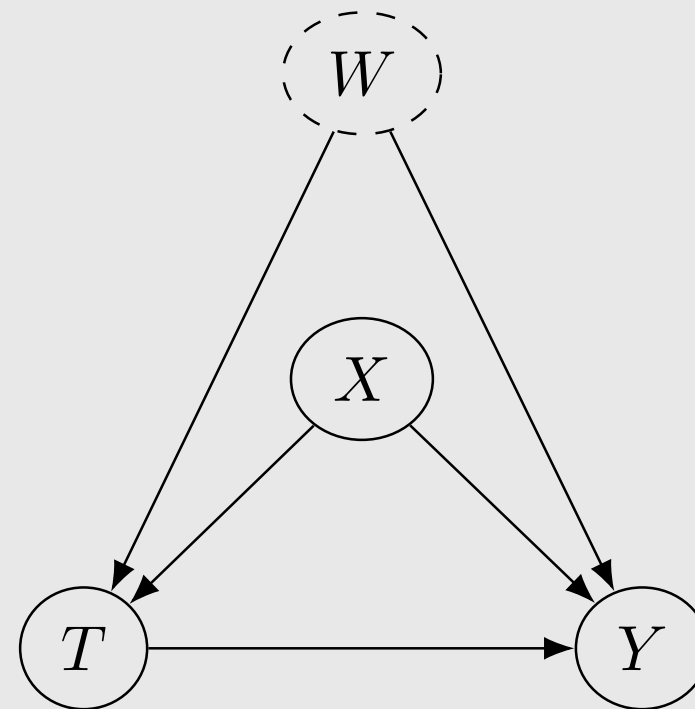


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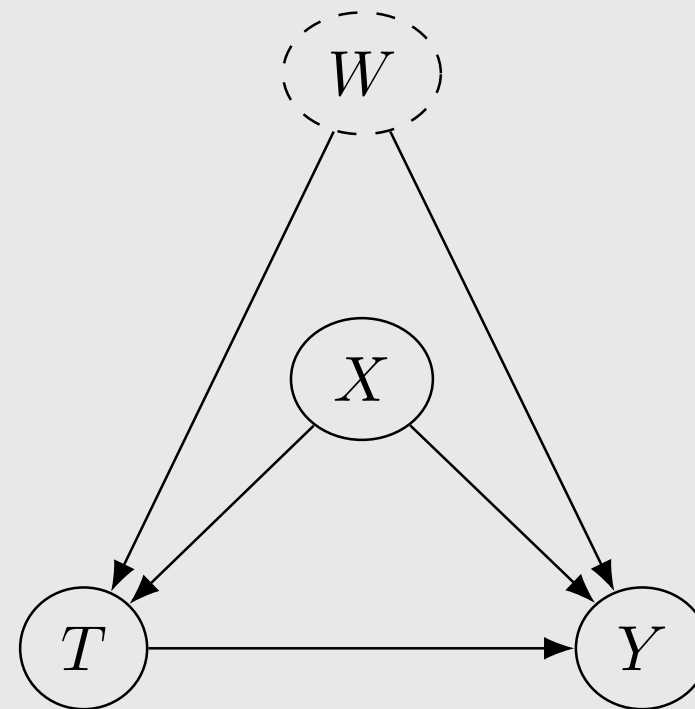


# Unconfoundedness is an untestable assumption

unconfoundedness = conditional ignorability = conditional exchangeability

Conditional exchangeability:

$$(Y(1), Y(0)) \not\perp\!\!\!\perp T \mid X$$





# Positivity

For all values of covariates  $x$  present in the population of interest (i.e.  $x$  such that  $P(X = x) > 0$ ),

$$0 < P(T = 1 \mid X = x) < 1$$

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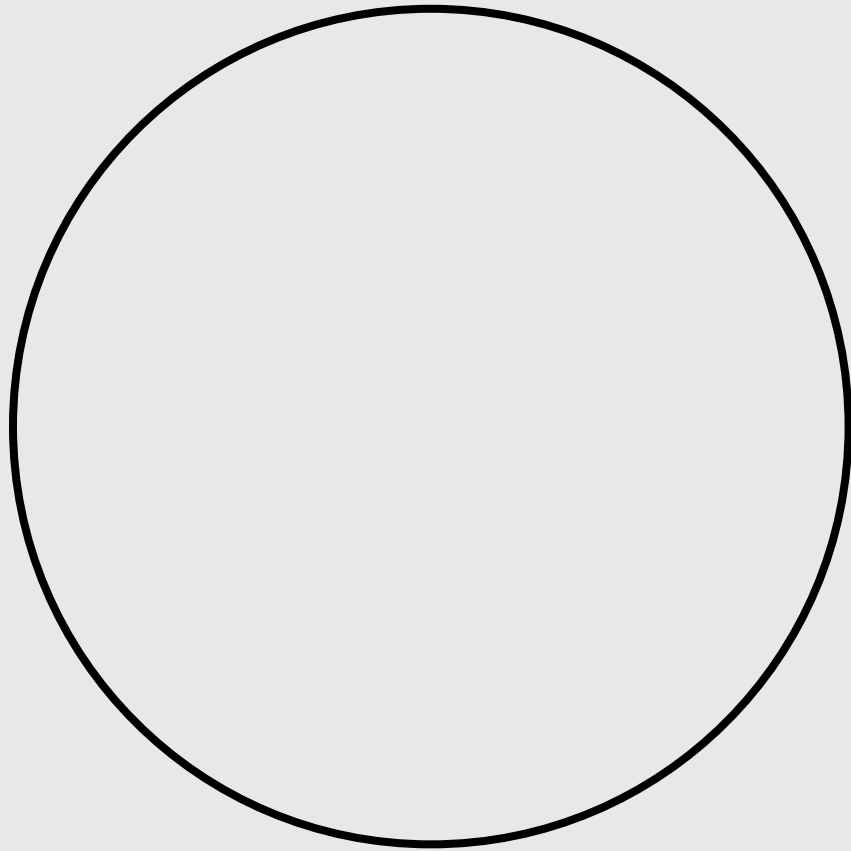
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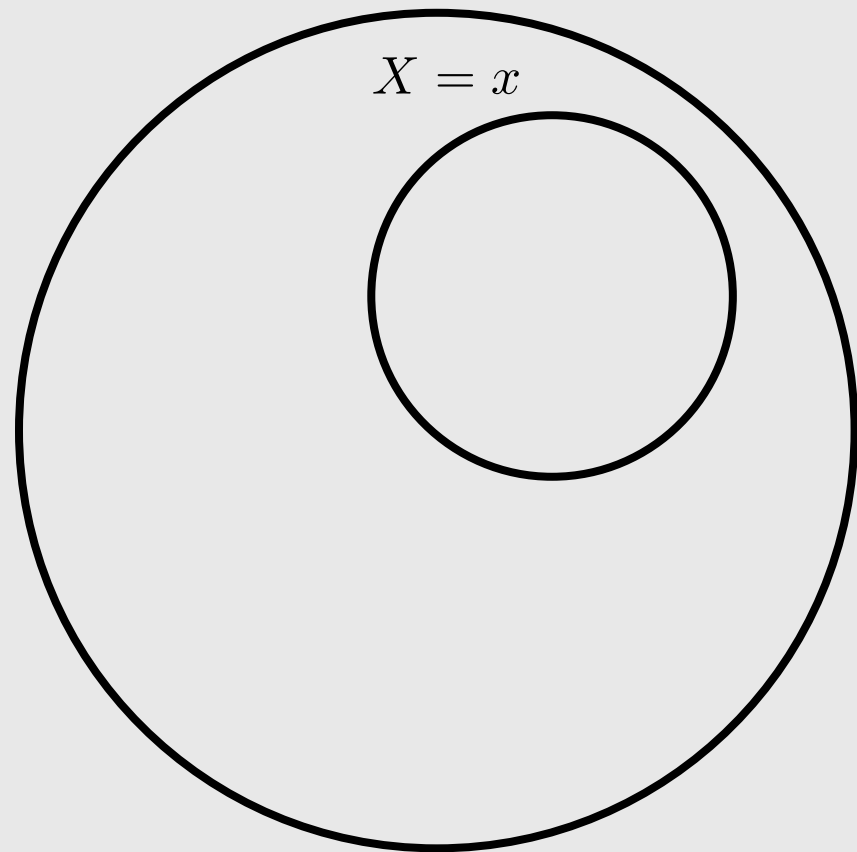
# Positivity: intuition

Total population



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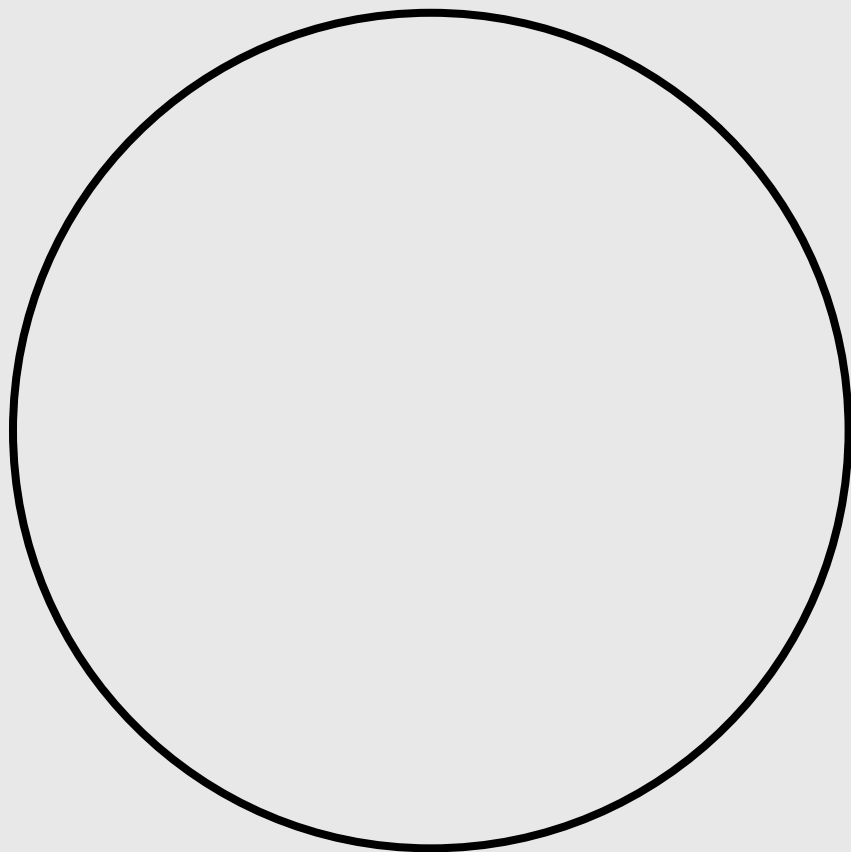
Total population



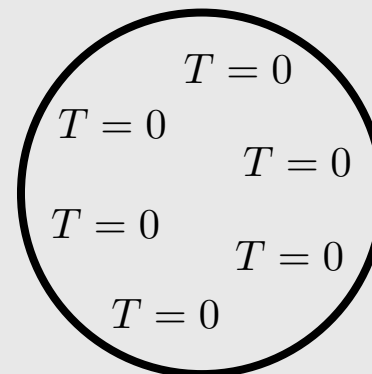


# Positivity: intuition

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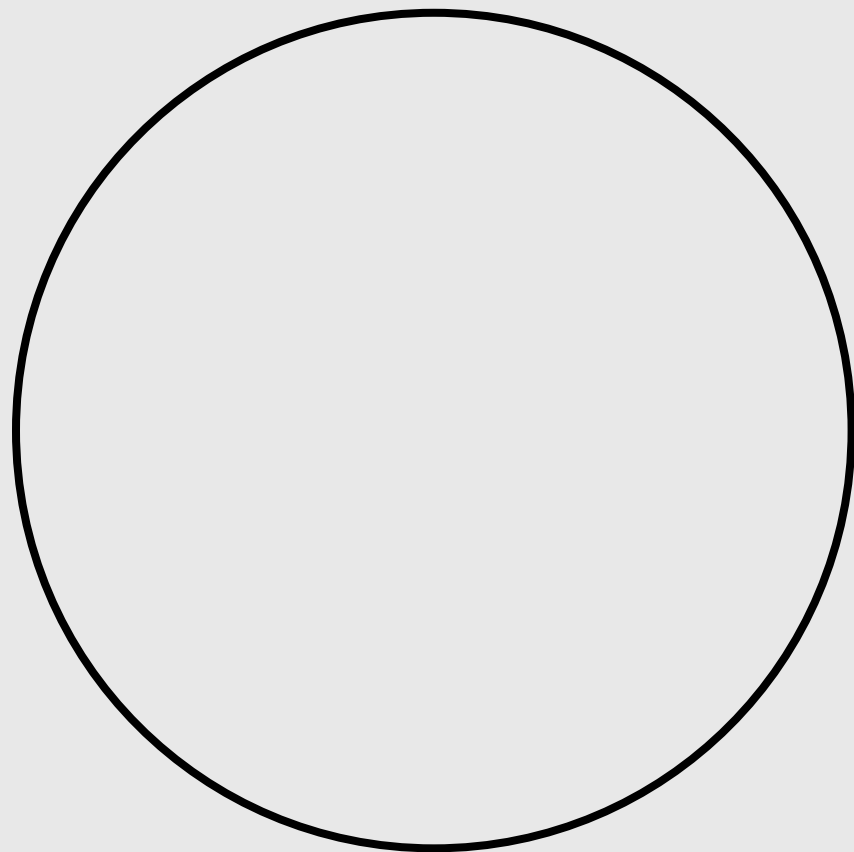
$X = x$



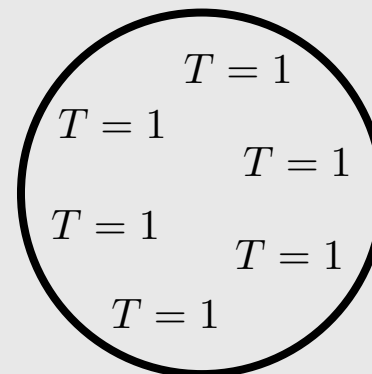
No one treated

# Positivity: intuition

Total population



$X = x$

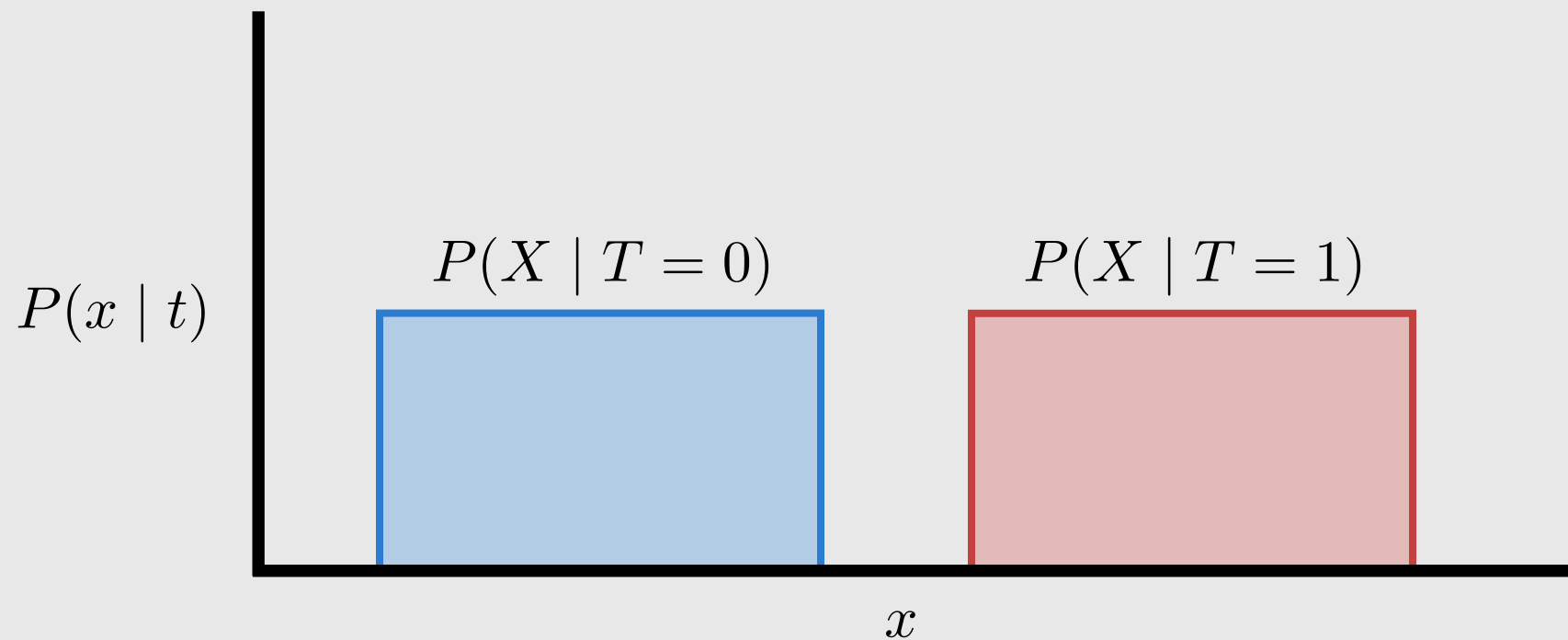


Everyone treated

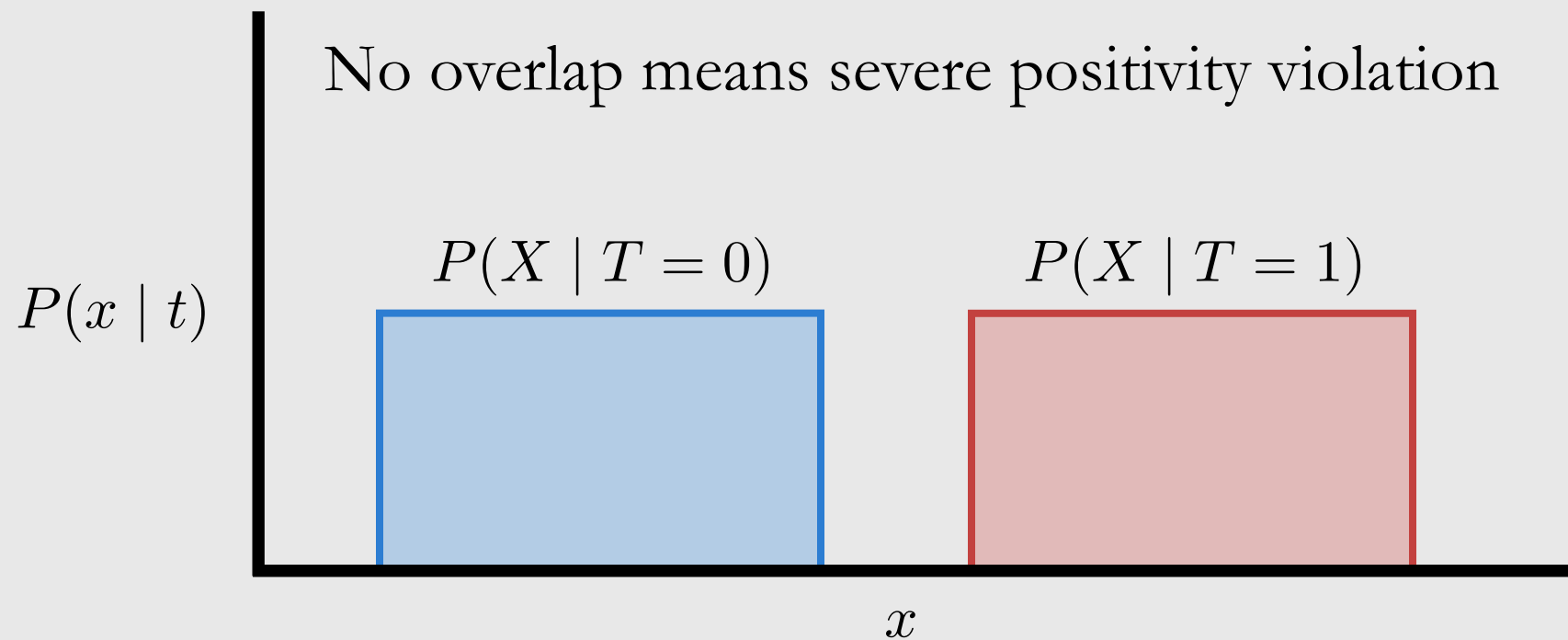
# Another perspective: overlap

Overlap between  $P(X | T = 0)$  and  $P(X | T = 1)$

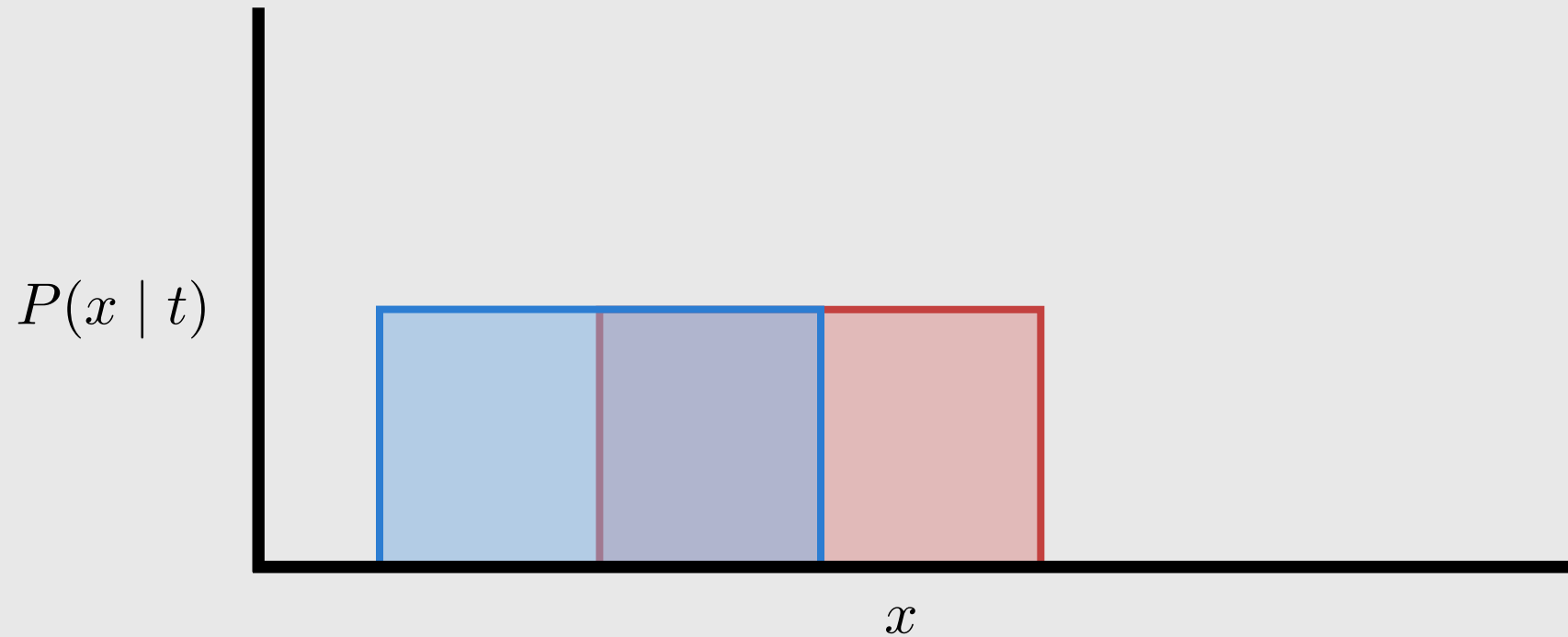
# Another perspective: overlap



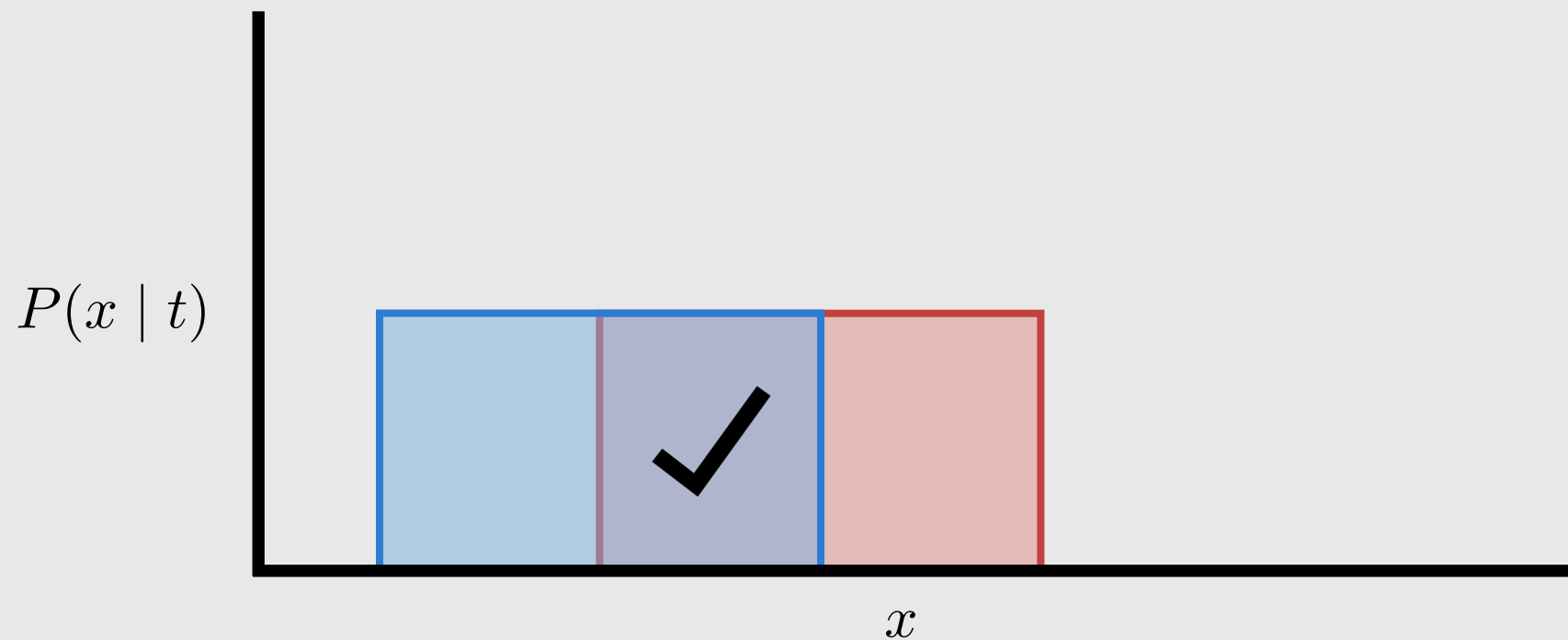
# Another perspective: overlap



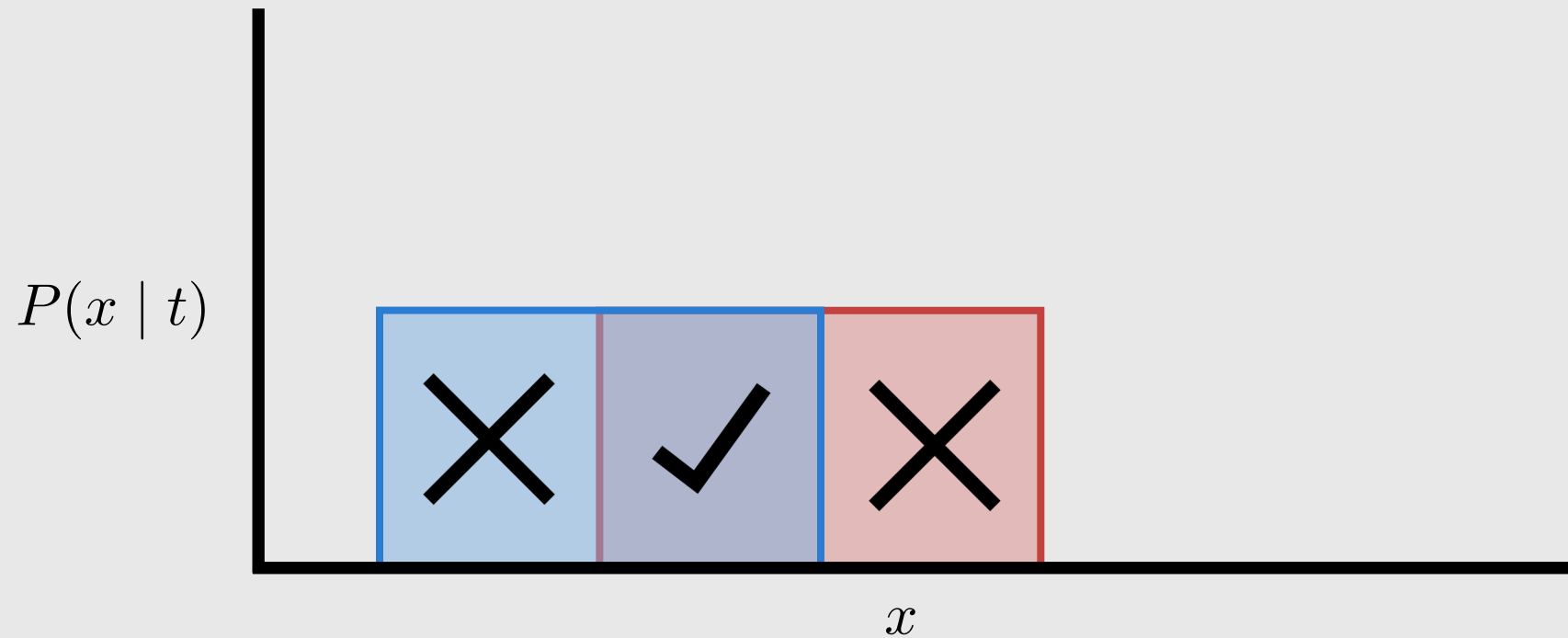
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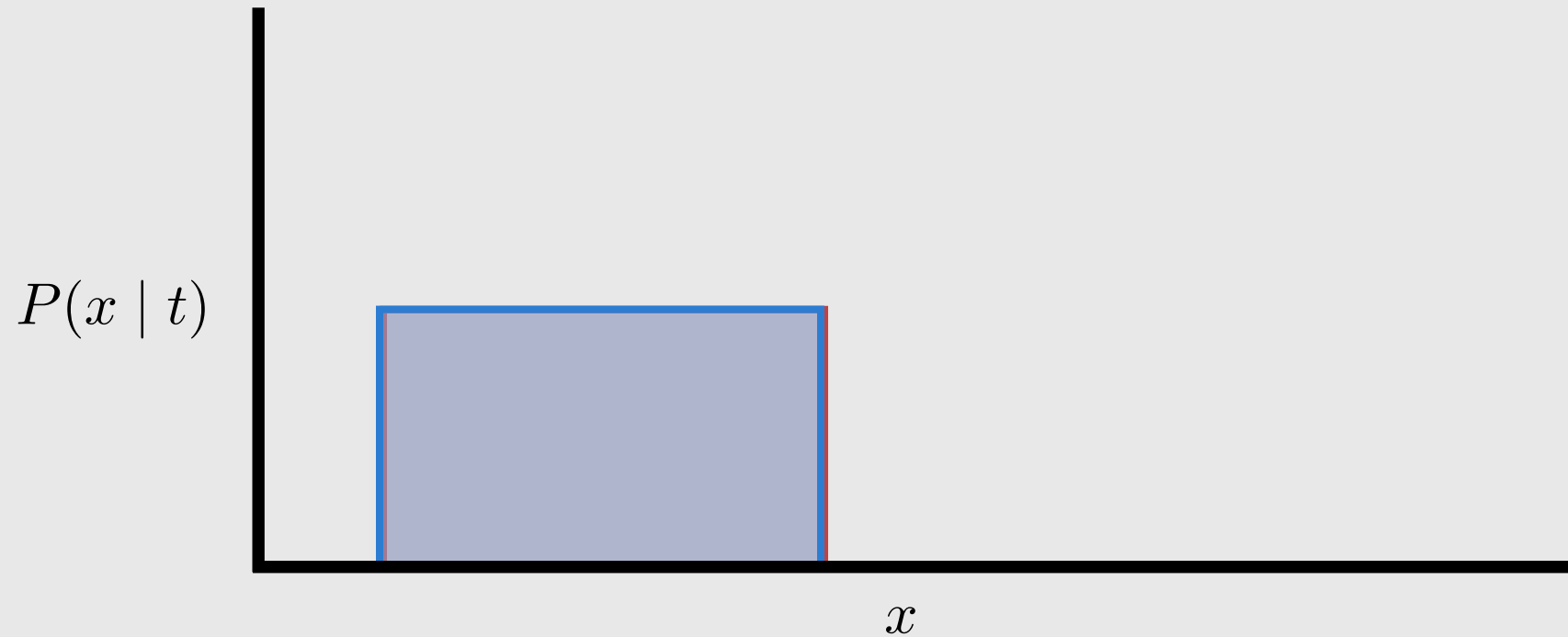


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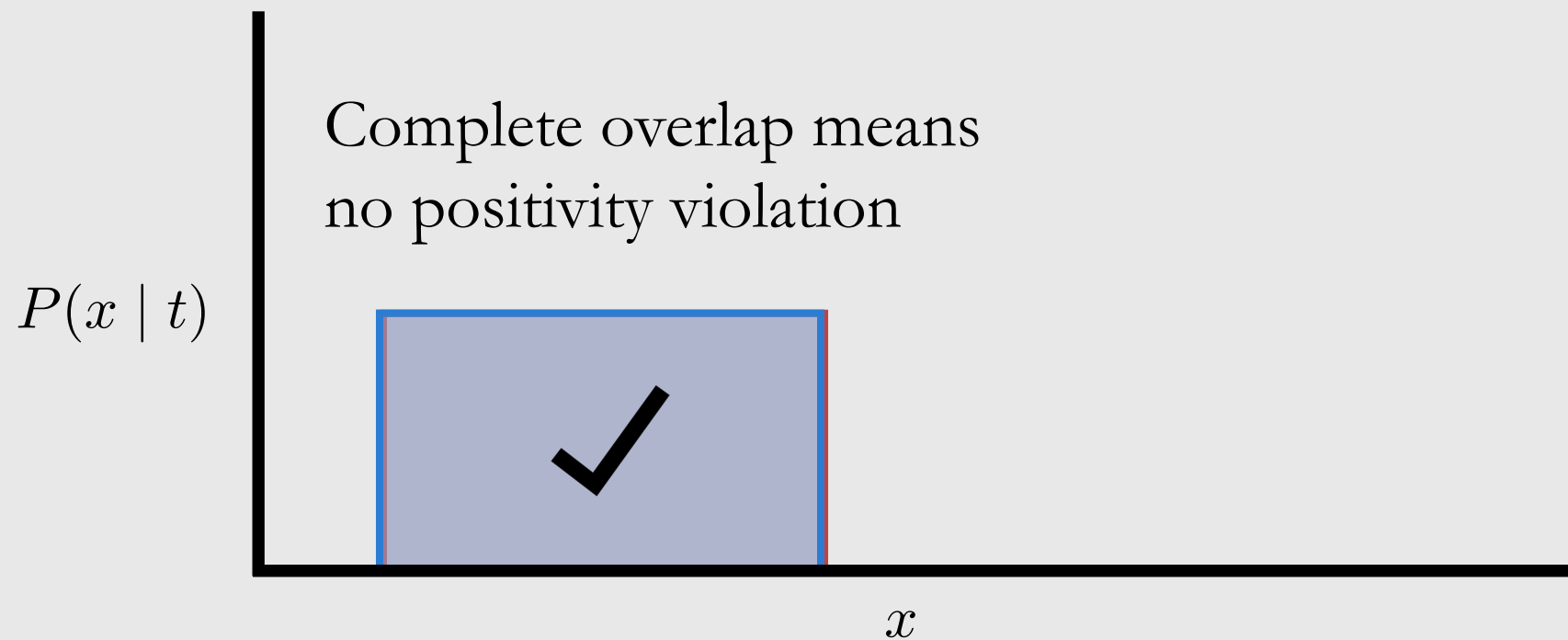




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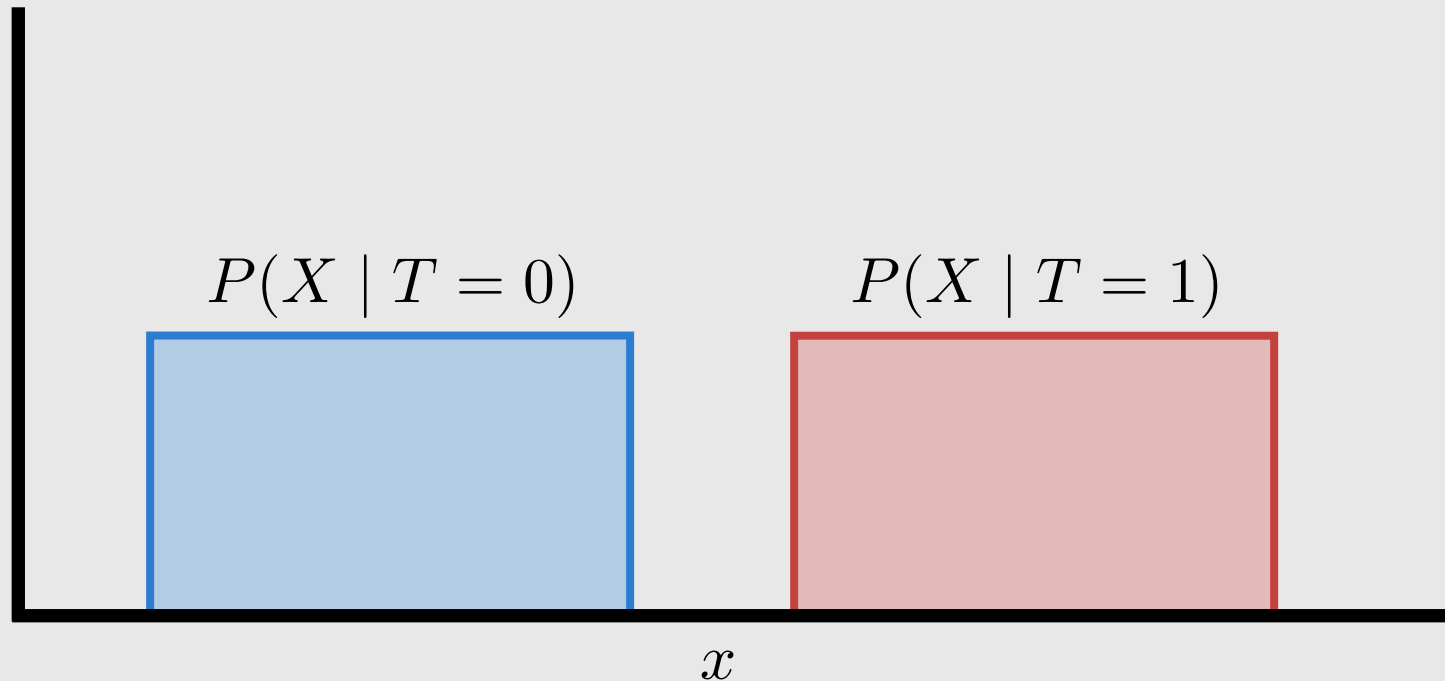
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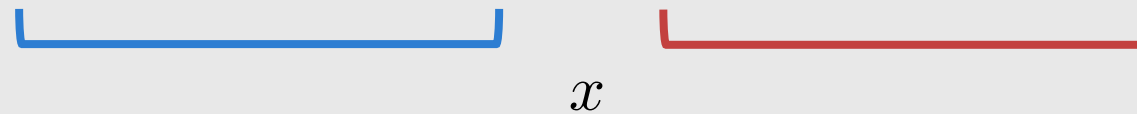
Question:

What goes wrong if we don't have  
positivity?

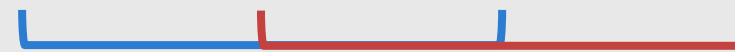
# The Positivity-Unconfoundedness Tradeoff



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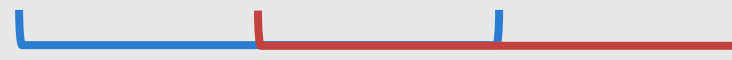
# The Positivity-Unconfoundedness Tradeoff



50% overlap

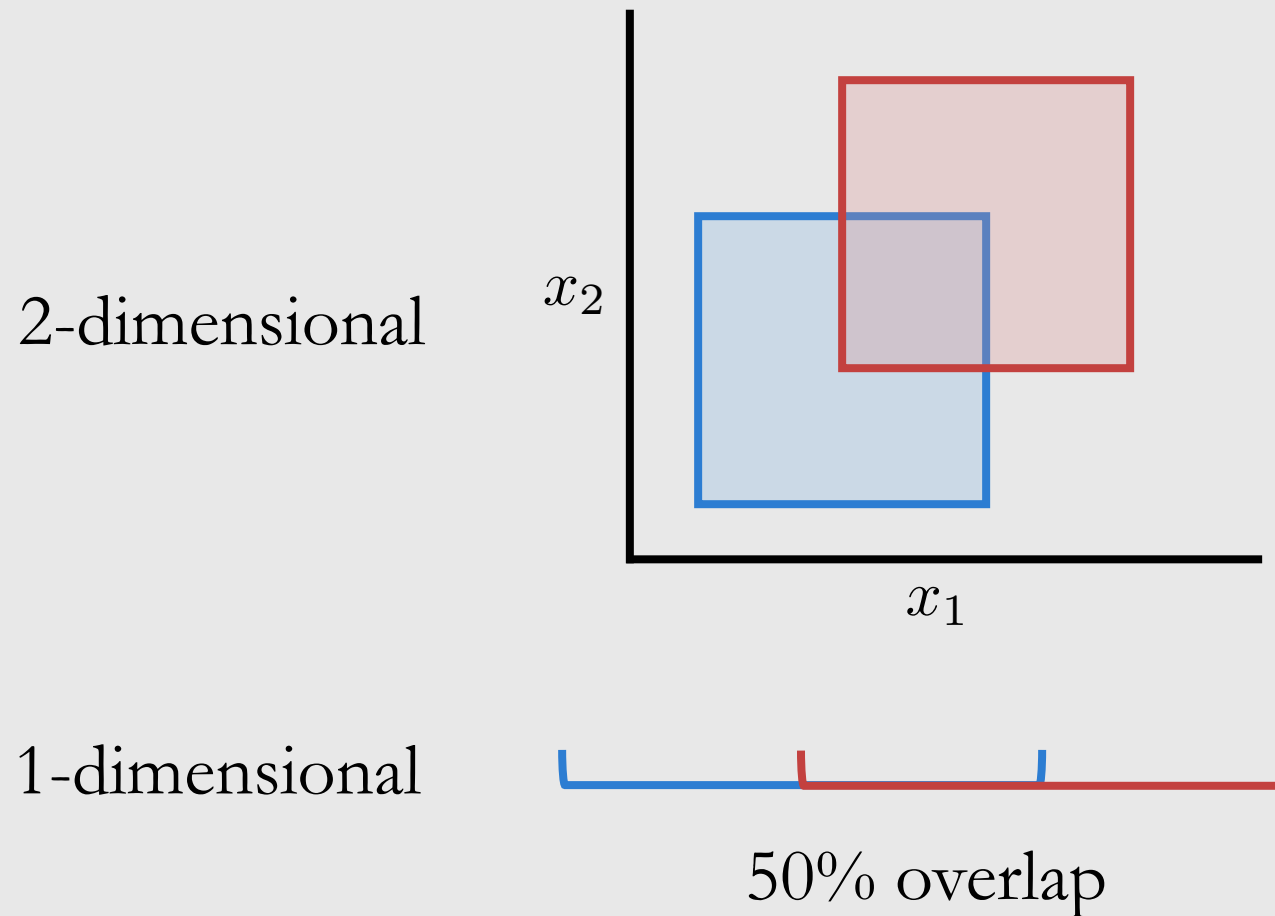
# The Positivity-Unconfoundedness Tradeoff

1-dimensional



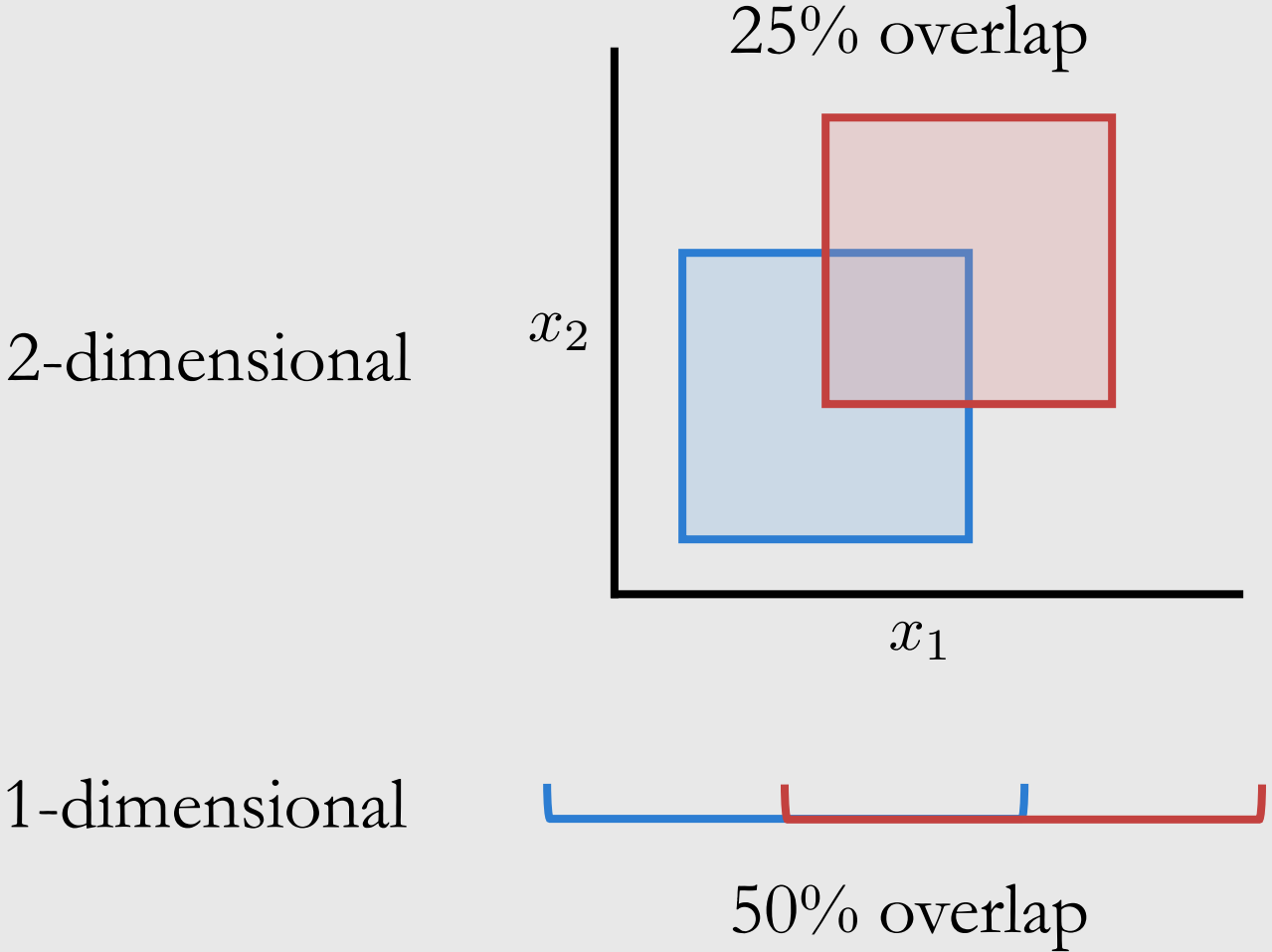
50% overlap

# The Positivity-Unconfoundedness Tradeoff

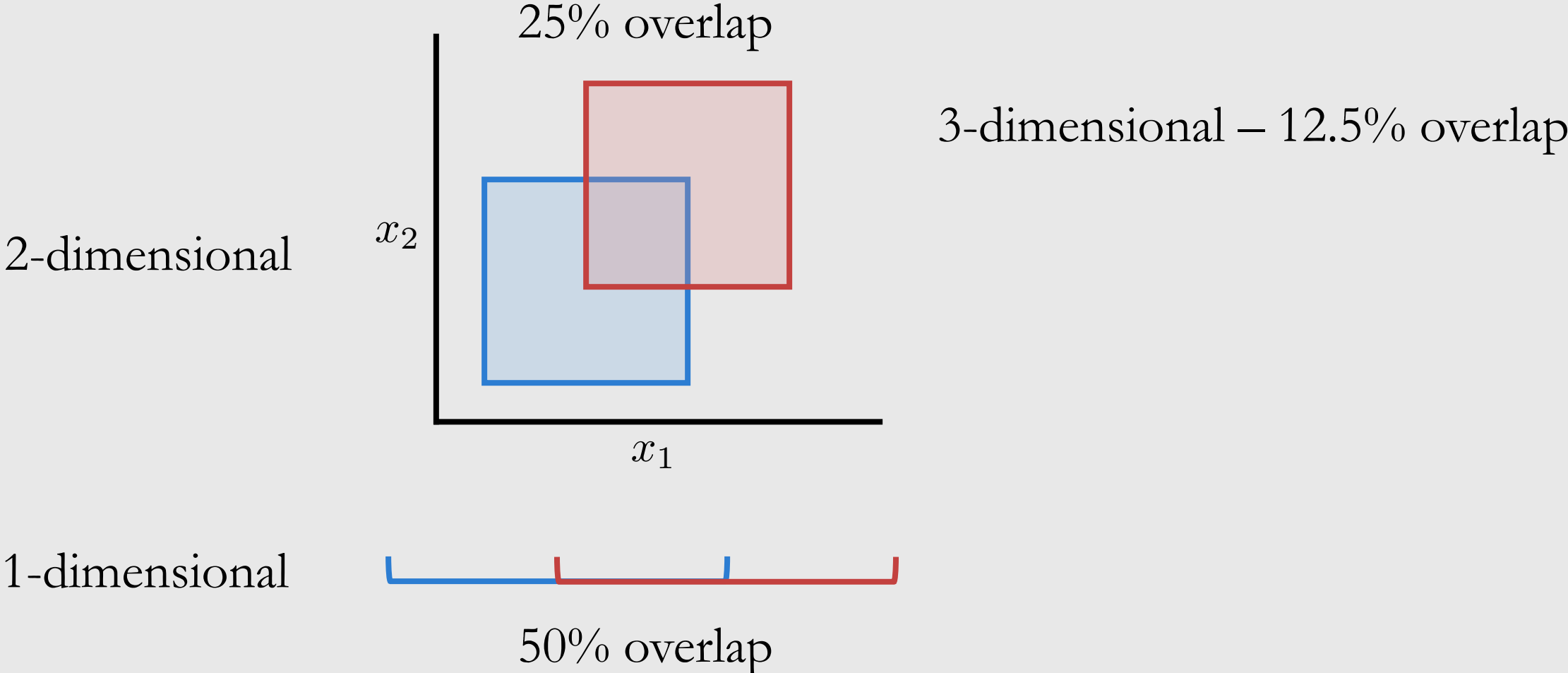




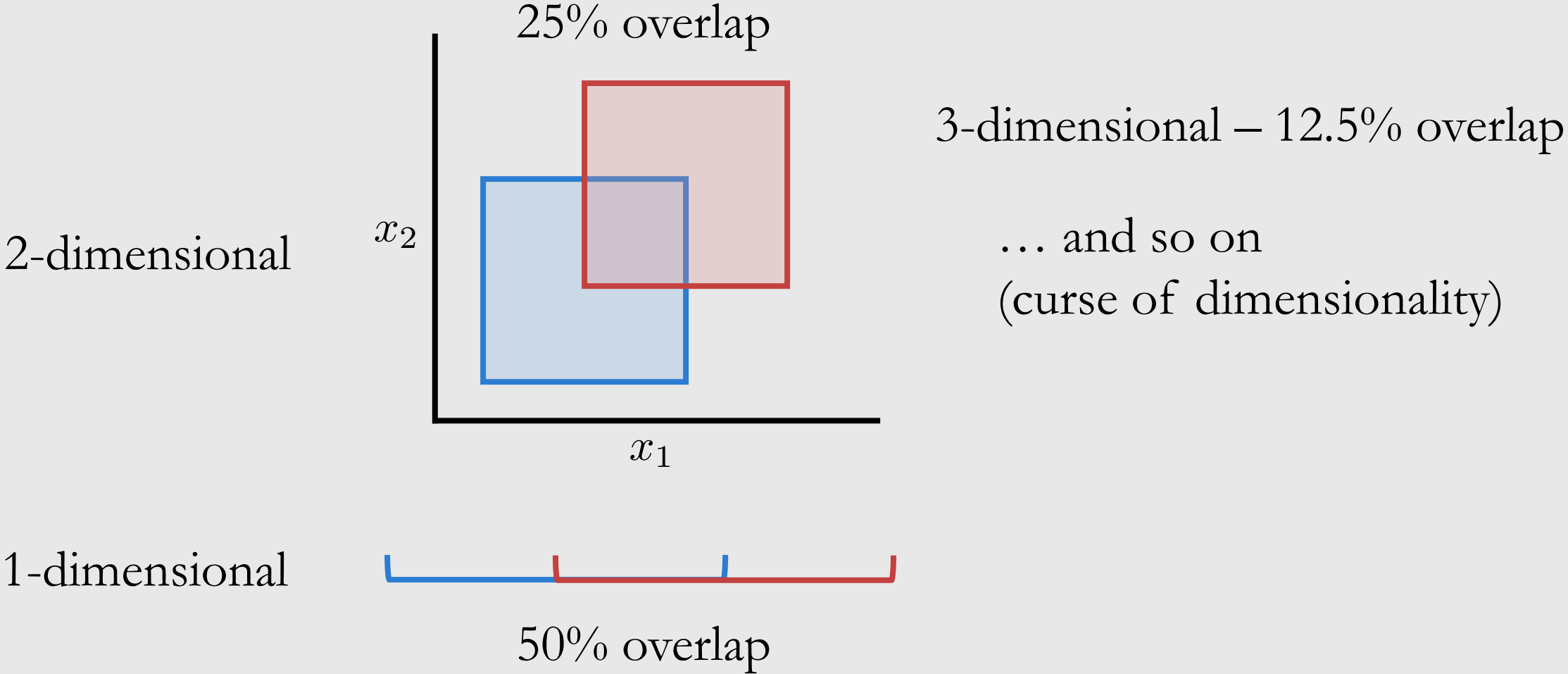
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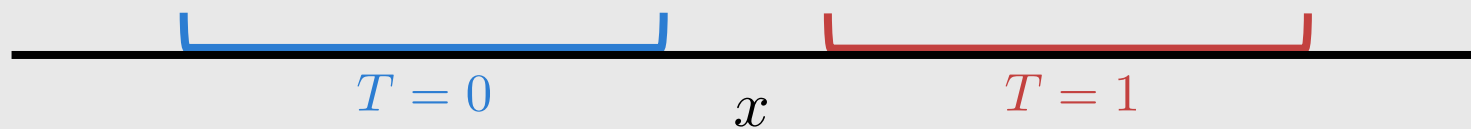
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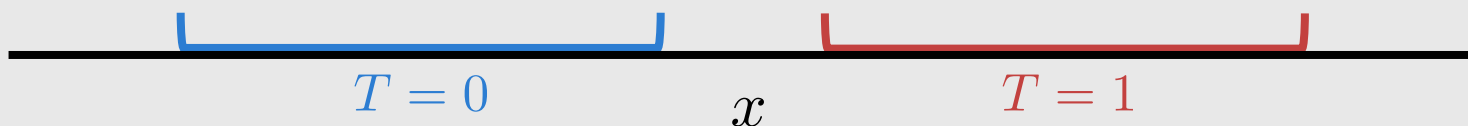


# Extrapolation



# Extrapolation

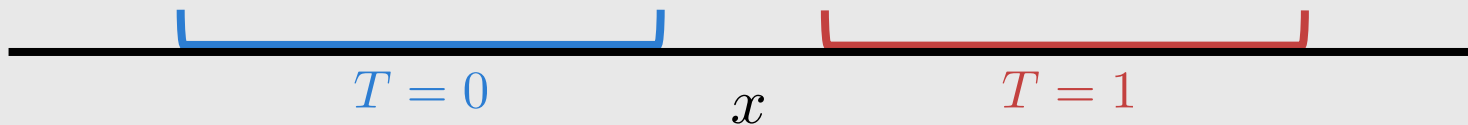
Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$



# Extrapolation

Adjustment formula:  $\sum_x$  (  $\mathbb{E}[Y \mid T = 1, x]$  -  $\mathbb{E}[Y \mid T = 0, x]$  )

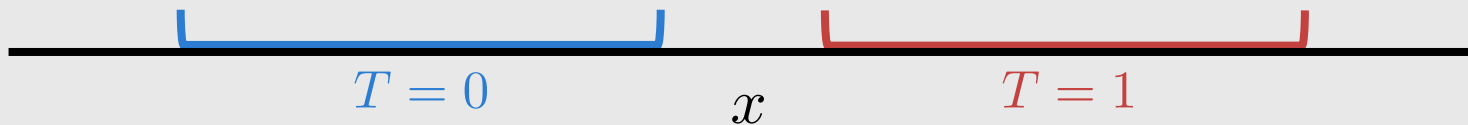
Model  
with  
 $f_1(x)$



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Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$

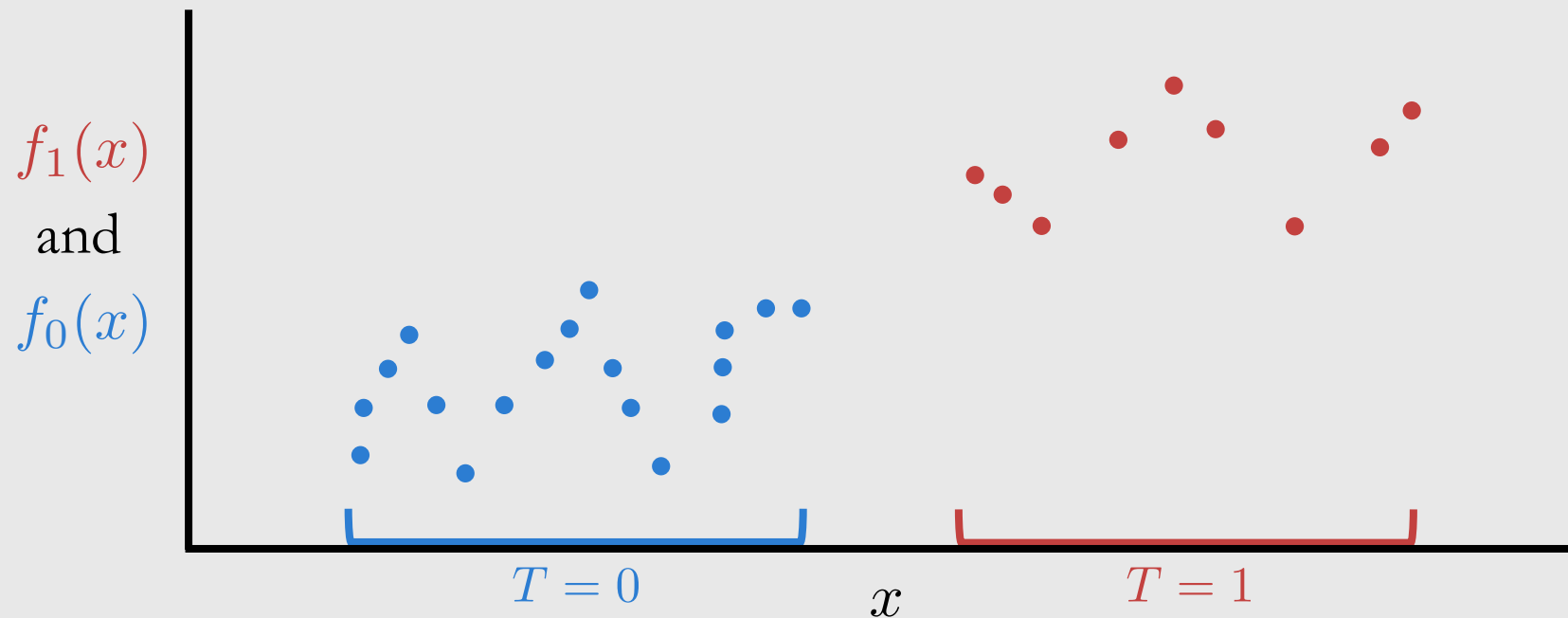
Model	Model
with $f_1(x)$	with $f_0(x)$



# Extrapolation

Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$

Model with  $f_1(x)$       Model with  $f_0(x)$

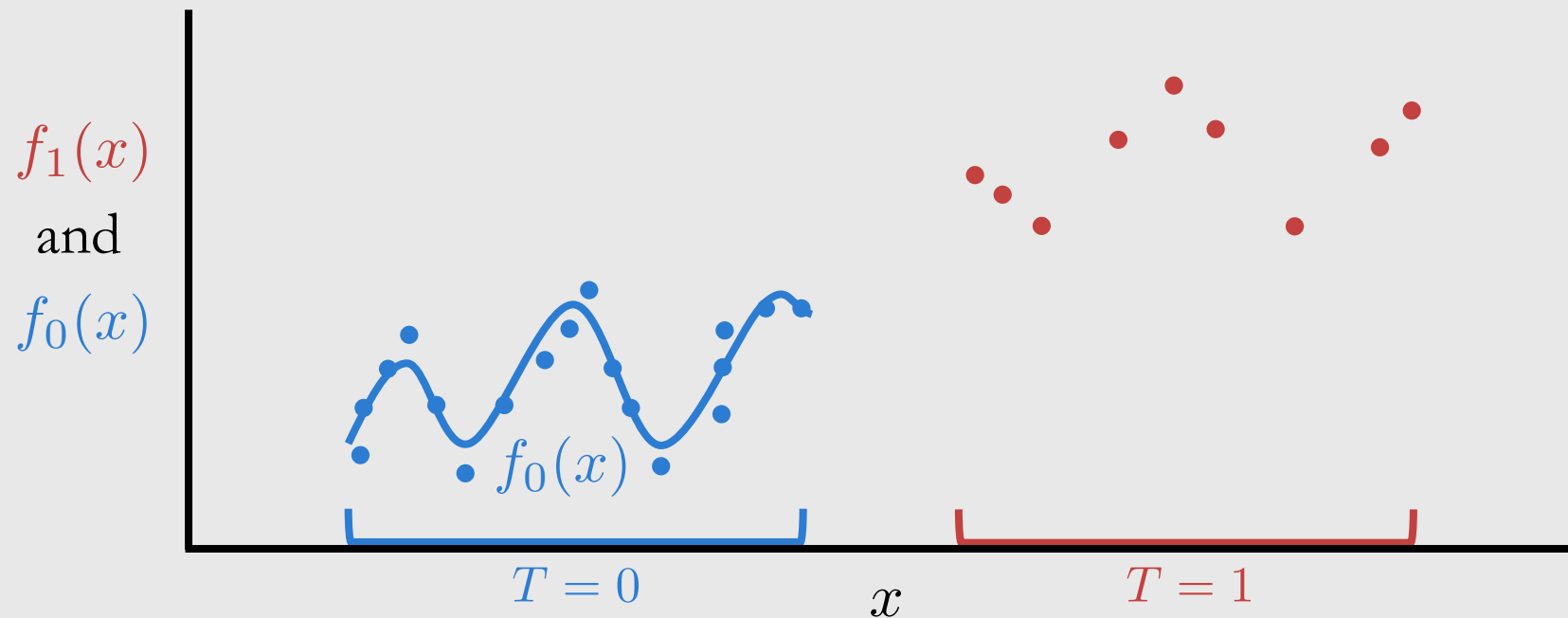




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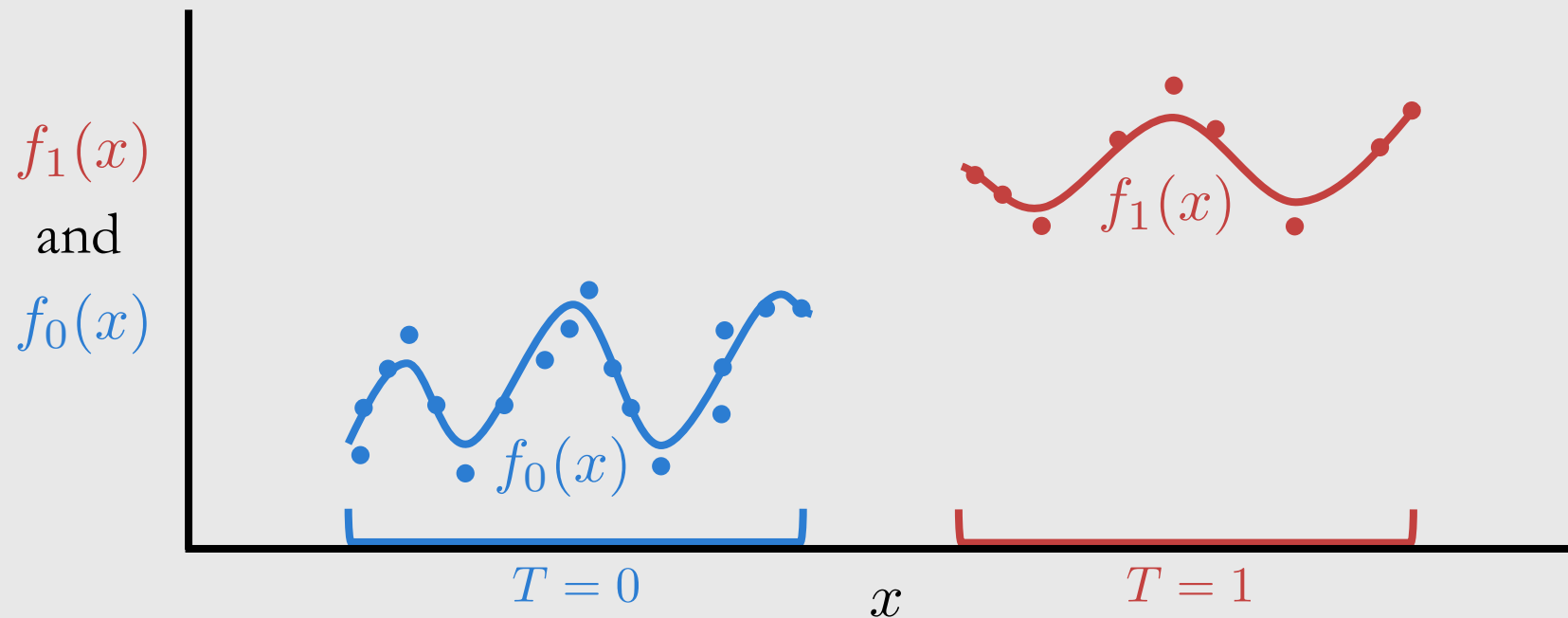
Model with  $f_1(x)$       Model with  $f_0(x)$



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Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$

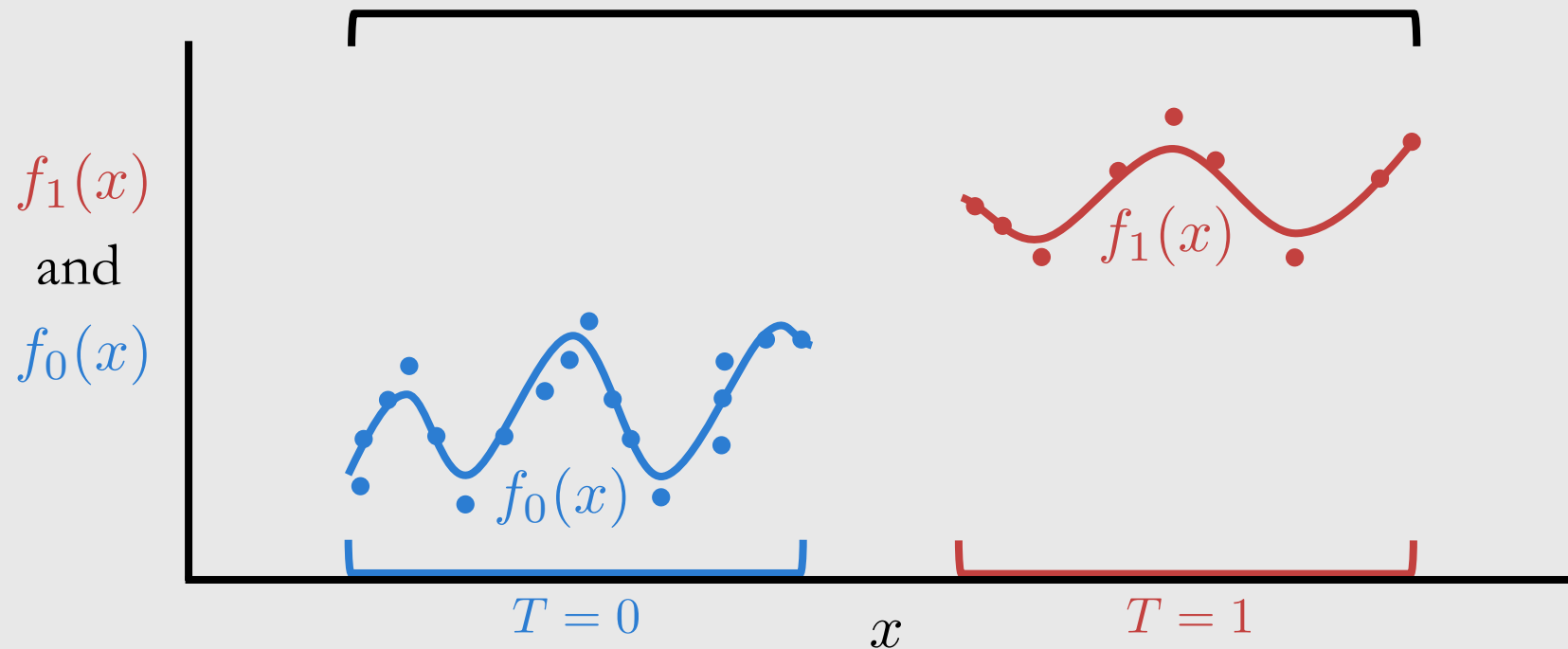
Model with  $f_1(x)$       Model with  $f_0(x)$



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Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$

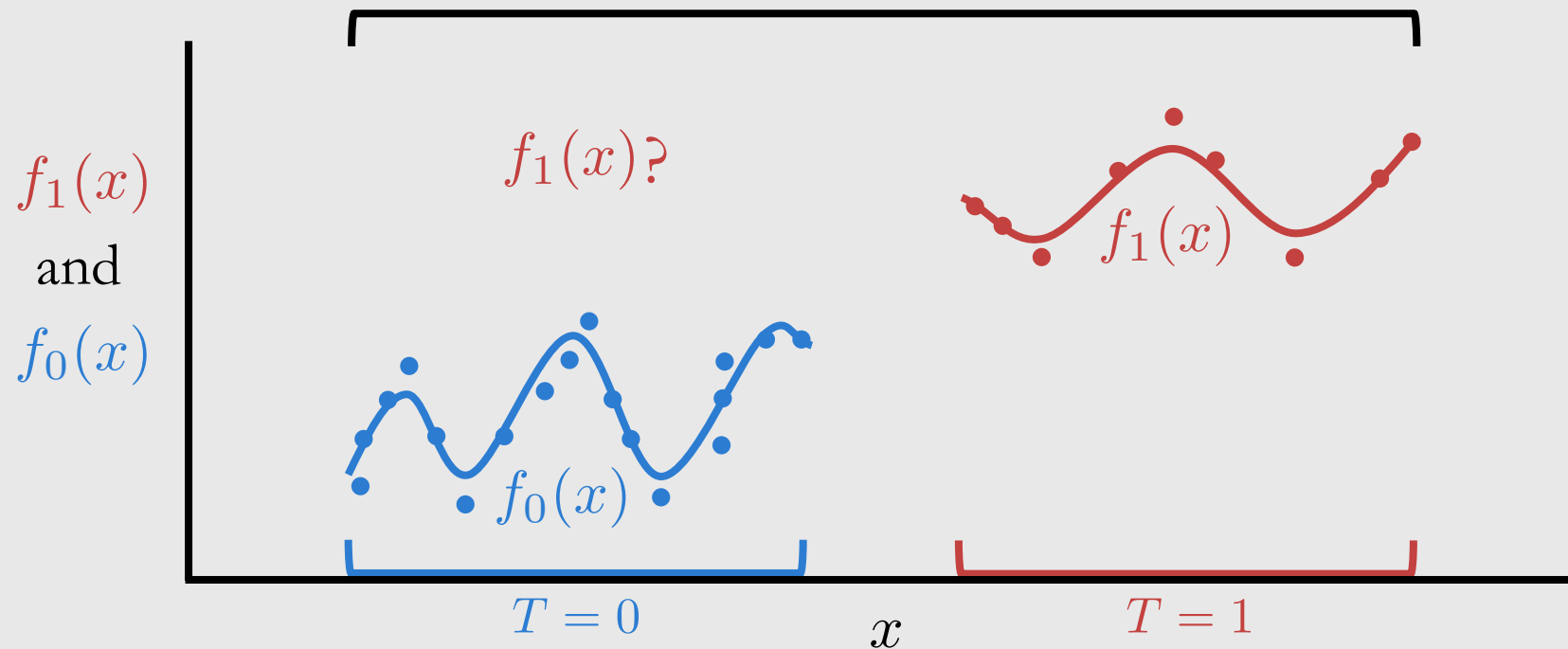
Model with  $f_1(x)$       Model with  $f_0(x)$



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Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$

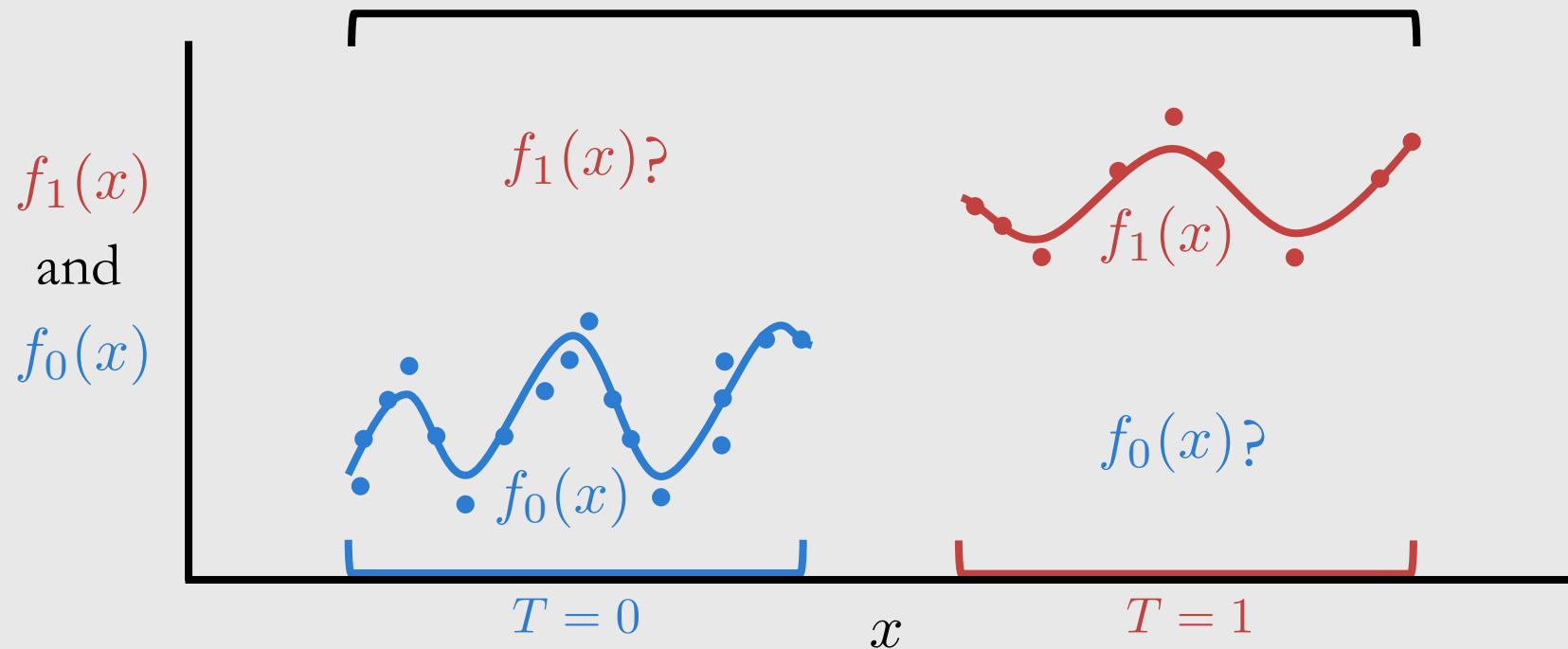
Model with  $f_1(x)$       Model with  $f_0(x)$



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Adjustment formula:  $\sum_x (\mathbb{E}[Y \mid T = 1, x] - \mathbb{E}[Y \mid T = 0, x])$

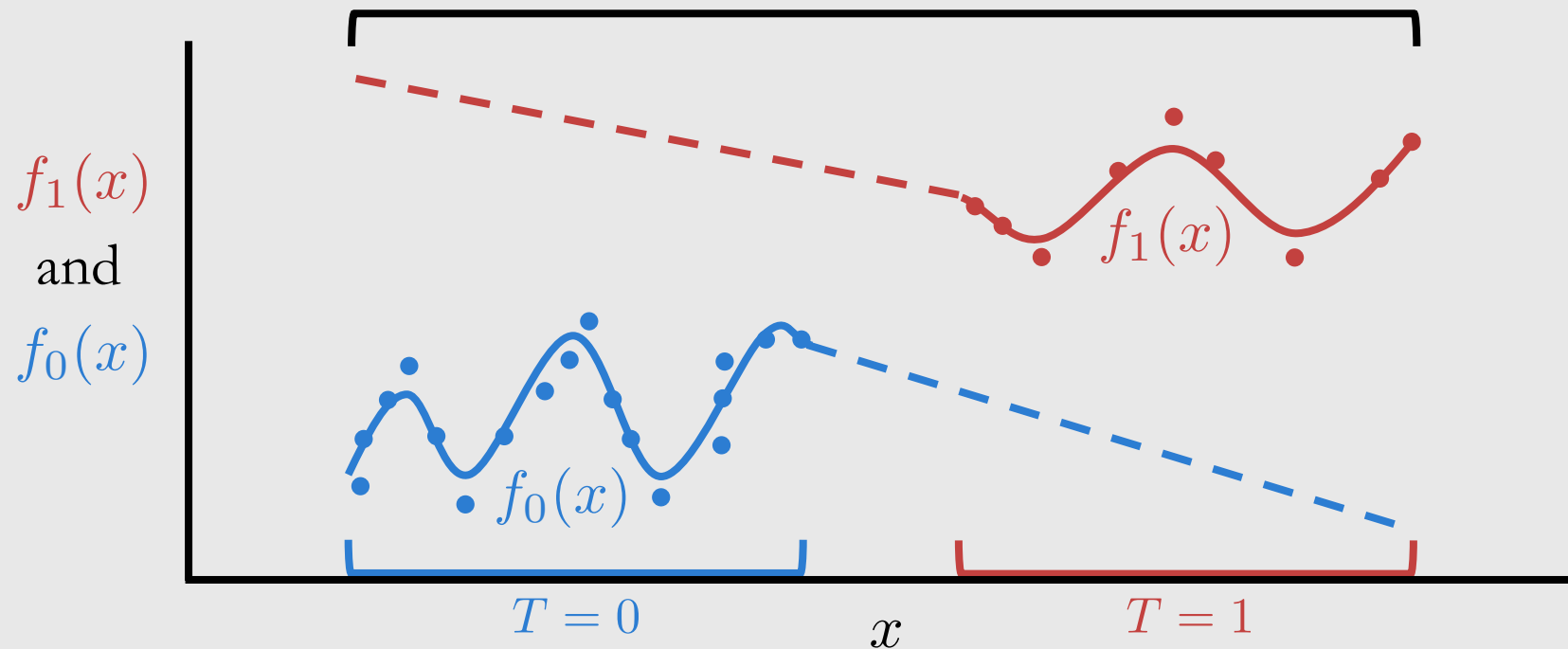
Model with  $f_1(x)$       Model with  $f_0(x)$



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Model with  $f_1(x)$       Model with  $f_0(x)$

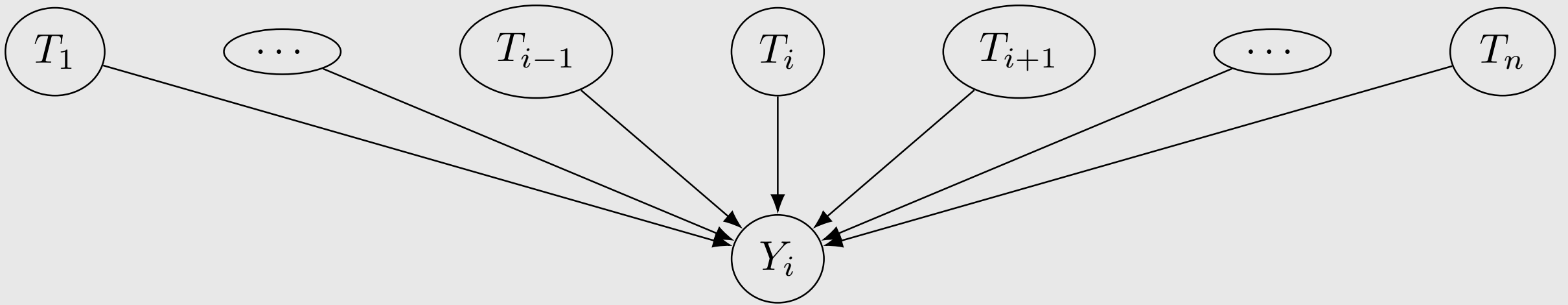


# No interference

$$Y_i(t_1, \dots, t_{i-1}, t_i, t_{i+1}, \dots, t_n) = Y_i(t_i)$$

# No interference

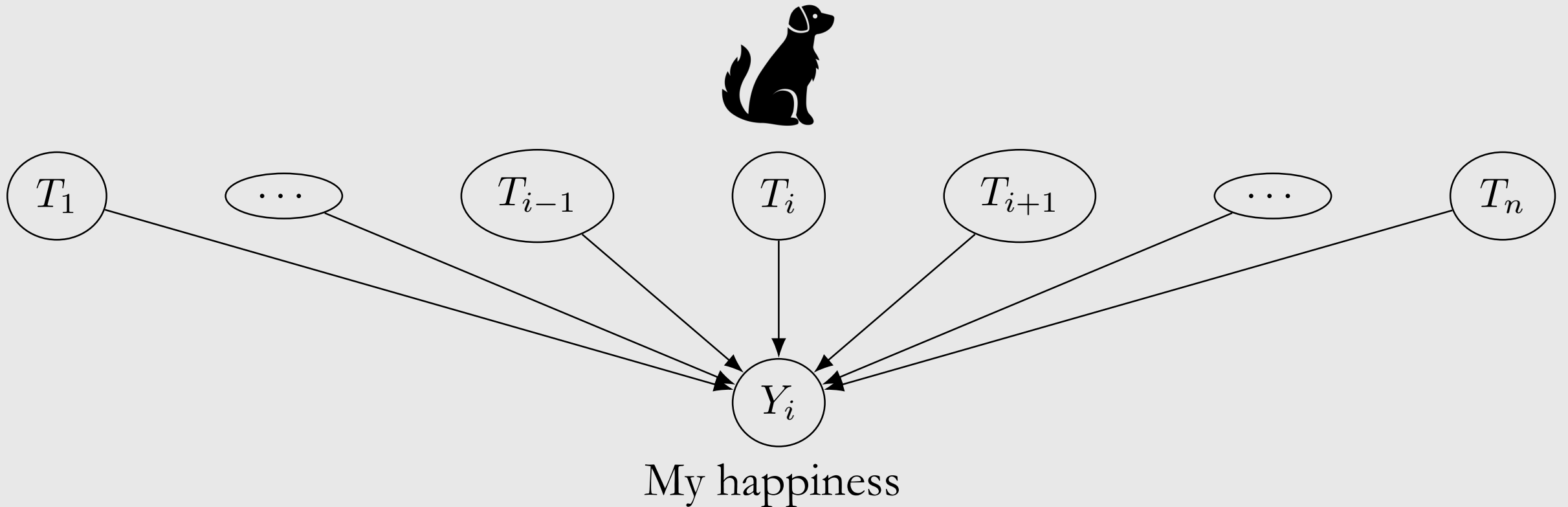
$$Y_i(t_1, \dots, t_{i-1}, t_i, t_{i+1}, \dots, t_n) = Y_i(t_i)$$





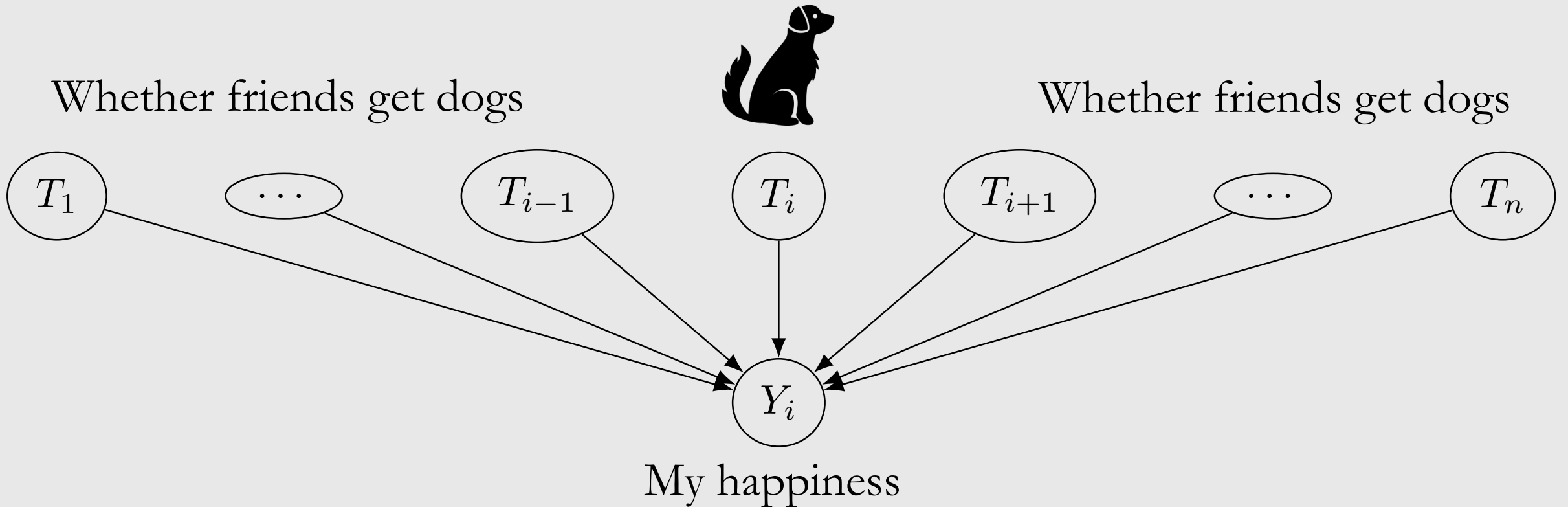
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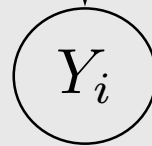
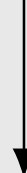
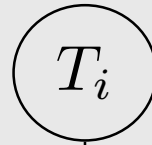
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My happiness

Consistency:  $T = t \implies Y = Y(t)$

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$T = 1$   
“I get a dog”

Consistency:  $T = t \implies Y = Y(t)$

$T = 1$   
“I get a dog”

$T = 0$   
“I don’t get a dog”

Consistency:  $T = t \implies Y = Y(t)$

$$T = 1$$

“I get a dog”

$$T = 0$$

“I don’t get a dog”



$(T = 1) \implies Y = 1$  (I’m happy)

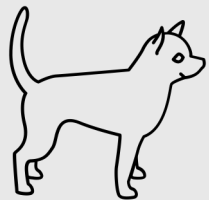
Consistency:  $T = t \implies Y = Y(t)$

$T = 1$   
“I get a dog”

$T = 0$   
“I don’t get a dog”



$(T = 1) \implies Y = 1$  (I’m happy)



$(T = 1) \implies Y = 0$  (I’m not happy)



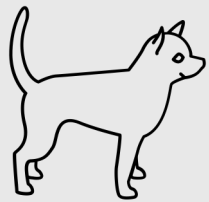
Consistency:  $T = t \implies Y = Y(t)$

$T = 1$   
“I get a dog”

$T = 0$   
“I don’t get a dog”



$(T = 1) \implies Y = 1$  (I’m happy)



$(T = 1) \implies Y = 0$  (I’m not happy)

Consistency assumption  
violated

Recall:

1. What were the four main assumptions?
2. Why do positivity violations require extrapolation?
3. Can you test if unconfoundedness is satisfied?
4. What is identifiability?

# Tying it all together

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

# Tying it all together

No interference



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

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

(linearity of expectation)

# Tying it all together

No interference



$$\begin{aligned}\mathbb{E}[Y(1) - Y(0)] &= \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] && \text{(linearity of expectation)} \\ &= \mathbb{E}_X [\mathbb{E}[Y(1) | X] - \mathbb{E}[Y(0) | X]] && \text{(law of iterated expectations)}\end{aligned}$$

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No interference



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No interference



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What are potential outcomes?

The fundamental problem of causal inference

Getting around the fundamental problem of causal inference

**A complete example with estimation**

# Estimands, estimates, and the Identification-Estimation Flowchart

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## The Identification-Estimation Flowchart





Problem: effect of sodium intake on blood pressure

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- Treatment  $T$ : sodium intake (1 if above 3.5 mg and 0 if below)
- Covariates  $X$ : age and amount of protein excreted in urine
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True ATE:  $\mathbb{E}[Y(1) - Y(0)] = 1.05$



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Estimate: 0.85

Naive:  $\mathbb{E}[Y | T = 1] - \mathbb{E}[Y | T = 0]$

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Estimate: 0.85  $\frac{|0.85 - 1.05|}{1.05} \times 100\% = 19\%$

Naive:  $\mathbb{E}[Y | T = 1] - \mathbb{E}[Y | T = 0]$

Naive estimate: 5.33  $\frac{|5.33 - 1.05|}{1.05} \times 100\% = 407\%$

# Using coefficient of linear regression

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Continuous treatment:  $\mathbb{E}[Y(1) - Y(0)]$

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Severe limitations:

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Severe limitations: the causal effect is the same for all individuals

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Run linear regression:  $Y = \hat{\alpha}T + \hat{\beta}X$        $\hat{\alpha} = 0.85$

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Severe limitations: the causal effect is the same for all individuals

$$Y_i(t) = \alpha t + \beta x_i$$

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Assume linear parametric form:  $Y = \alpha T + \beta X$

Run linear regression:  $Y = \hat{\alpha}T + \hat{\beta}X$        $\hat{\alpha} = 0.85$

Continuous treatment:  $\mathbb{E}[Y(t)]$    $\hat{\alpha} = 0.85$


Severe limitations: the causal effect is the same for all individuals

$$Y_i(t) = \alpha t + \beta x_i \qquad Y_i(1) - Y_i(0) = \alpha \cdot 1 + \beta x_i \\ \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad -\alpha \cdot 0 - \beta x_i$$

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# Using coefficient of linear regression

Assume linear parametric form:  $Y = \alpha T + \beta X$

Run linear regression:  $Y = \hat{\alpha}T + \hat{\beta}X$        $\hat{\alpha} = 0.85$

Continuous treatment:  $\mathbb{E}[Y(t)] \longrightarrow \hat{\alpha} = 0.85$

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See Sections 6.2 and 6.3 of [Morgan & Winship \(2014\)](#) for more complete critique