Resources mainly from Brady Neal's "Introduction to Causal Inference" and Marcelo Coca Perraillon's "Week 2: Causal Inference"

Concepts & Important Topics in Causal Learning

Wed. reading group

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Concepts & Important Topics

1. *Why does causal inference matter?*
   a. *What is causal inference?*
   b. *Simpson's paradox*
   c. *Confounders, Potential outcomes, Individual Treatment Effect (ITE)*

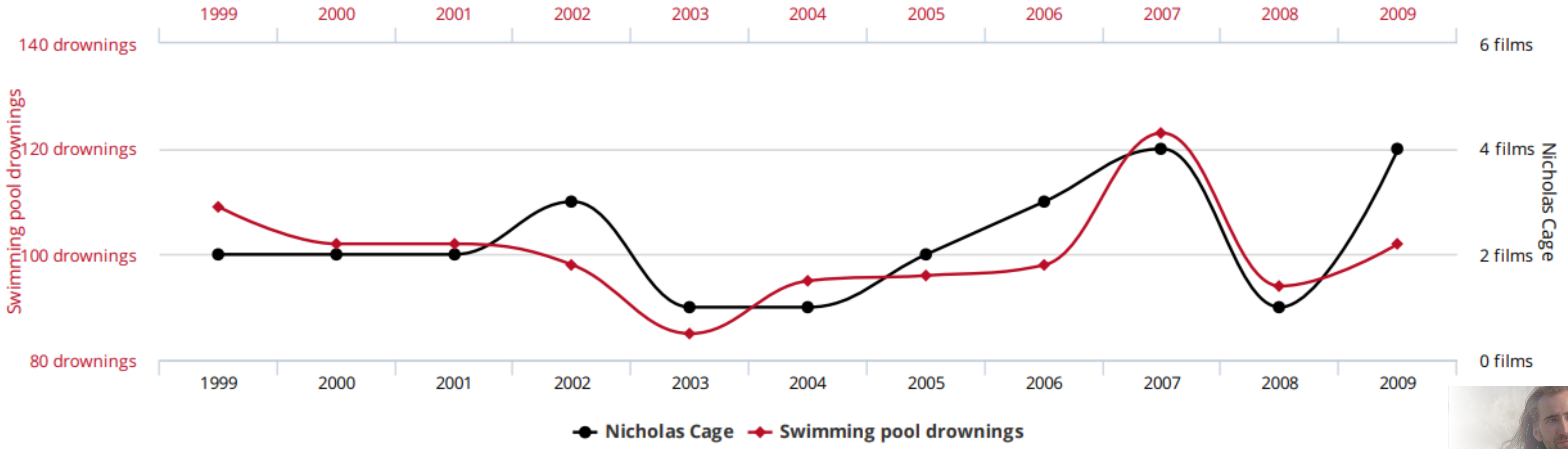
2. *The fundamental problem of causal inference*
   a. *Factuals & Counterfactuals*
   b. *How to avoid the fundamental problem of causal inference*
   c. *The flowchart of causal inference*

Why does causal inference matter?

What is causal inference?

- Causation: Refers to the relationship between **cause** and **effect**.
  - "A happened because of B"
  - "B happened, therefore A has happened as a result"
  - Heavily used in economics, medical research, and recently, **machine learning**.

- "Correlation does not imply Causation"
  - Critical difference between statistic association and causal association.
  - Example data: Nicholas Cage vs. Swimming pool drownings
  - *Did Nicholas Cage **cause** the national swimming pool drowning pandemic?*



Why does causal inference matter?

Simpson's paradox

- Knowing the causal structure of the data provides a deep understanding of the problem.
- Example dataset: Administering a drug to cure a patient

Table: Rate of death in patients after drug administeration.

Treatment =
What type of drug? (A or B)

Treatment	Condition: Mild	Condition: Severe	Condition: Total
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)
B	**10%** (5/50)	**20%** (100/500)	19% (105/550)

Looking at each conditions:
We should use drug B.

Looking at the 'total' data:
We should use drug A.

Which drug is more effective in reducing mortality rate?

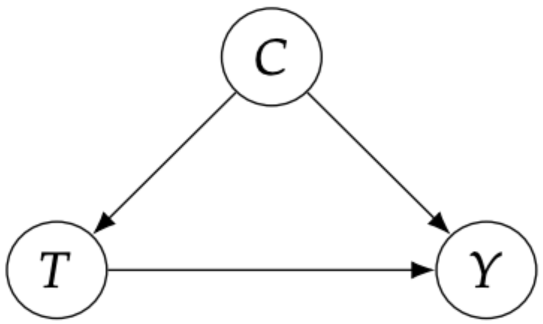
Why does causal inference matter?

Simpson's paradox

- Answer can be either A or B, **depending on the causal structure** of the problem.

C = Some cause | T = Treatment: 1 (A) or 0 (B) | Y = Mortality: 1 (live) or 0 (die)

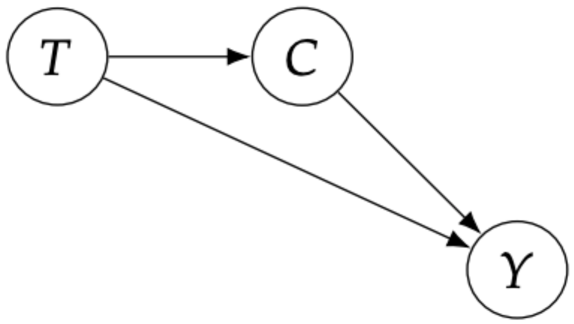
Scenario 1



C = Condition of the patient

- Example: Doctor prescribes drug based on patient's condition.
- (C = Mild)
  - Doctor prescribes drug A ($C \rightarrow T$)
  - Mild patients usually live ($C \rightarrow Y$)
  - vice versa
- Therefore, B is more effective in treating since the patients taking A probably has a mild condition in the first place.

Scenario 2

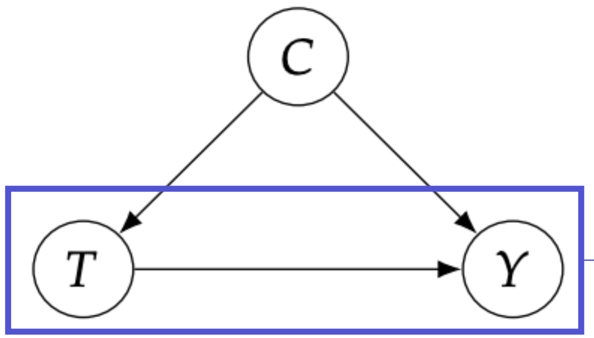


C = Development time of the disease

- Example: Drug B is so rare to find that it takes a long time to actually administer to the patient.
- (T = B)
  - Patient has to wait a long time to get the drug ($T \rightarrow C$)
  - Which reduces the chance of cure ($C \rightarrow Y$)
  - vice versa
- Therefore, A is more effective in treating since the patients don't need to wait too long to be cured.

Why does causal inference matter?

Confounders*, *Potential outcomes, Individual Treatment Effect (ITE)



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- Example: Doctor prescribes drug based on patient's condition.
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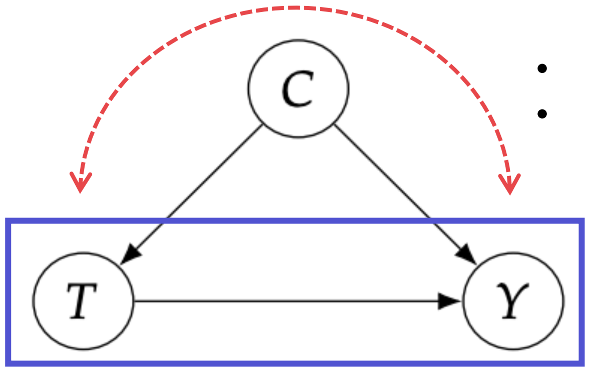
  - vice versa
- Therefore, B is more effective in treating since the patients taking A probably has a mild condition in the first place.

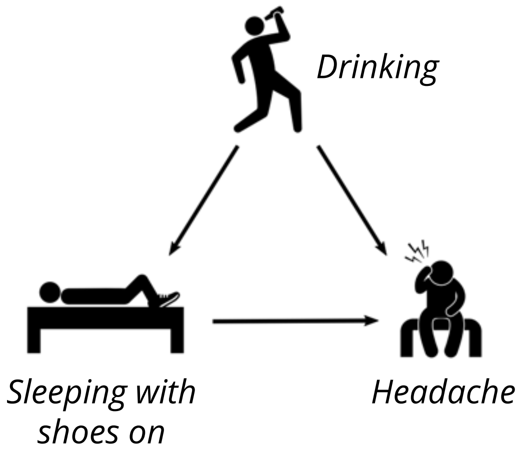
- This implies: When we only have data for T and Y, we may conclude a **causal relation** of $T \rightarrow Y$.
- However, there is **no guarantee** that is the case.
- There are definitely **statistical associations**.

Why does causal inference matter?

Confounders*, *Potential outcomes, Individual Treatment Effect (ITE)



- C is a **confounding variable**, causing a confounding association.
- Counfounding path: $T \leftarrow C \rightarrow Y$

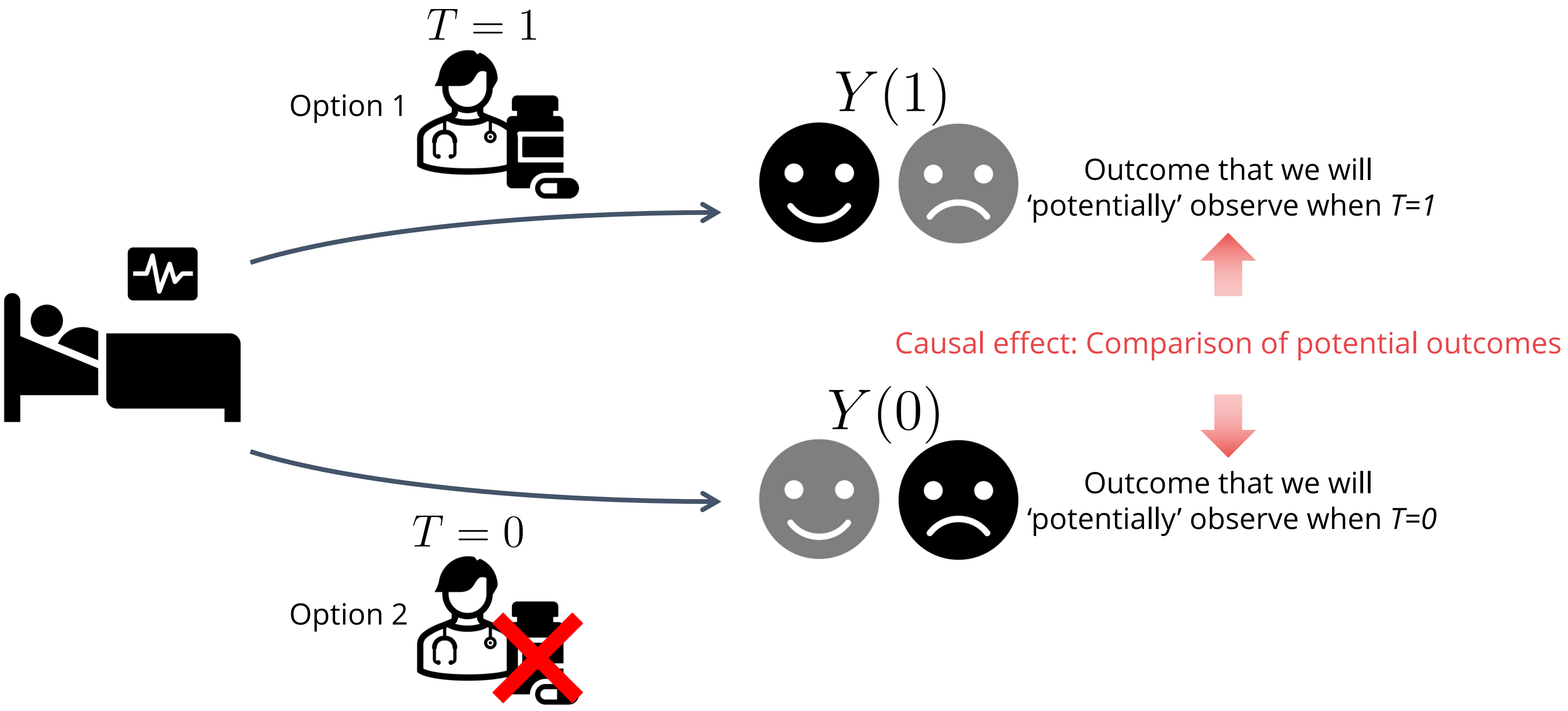


- This implies: When we only have data for T and Y, we may conclude a **causal relation** of $T \rightarrow Y$.
- However, there is **no guarantee** that is the case.
- There are definitely **statistical associations**.
- **Main problem: How can we turn causal associations into statistical associations?**

Why does causal inference matter?

Confounders, Potential outcomes, Individual Treatment Effect (ITE)

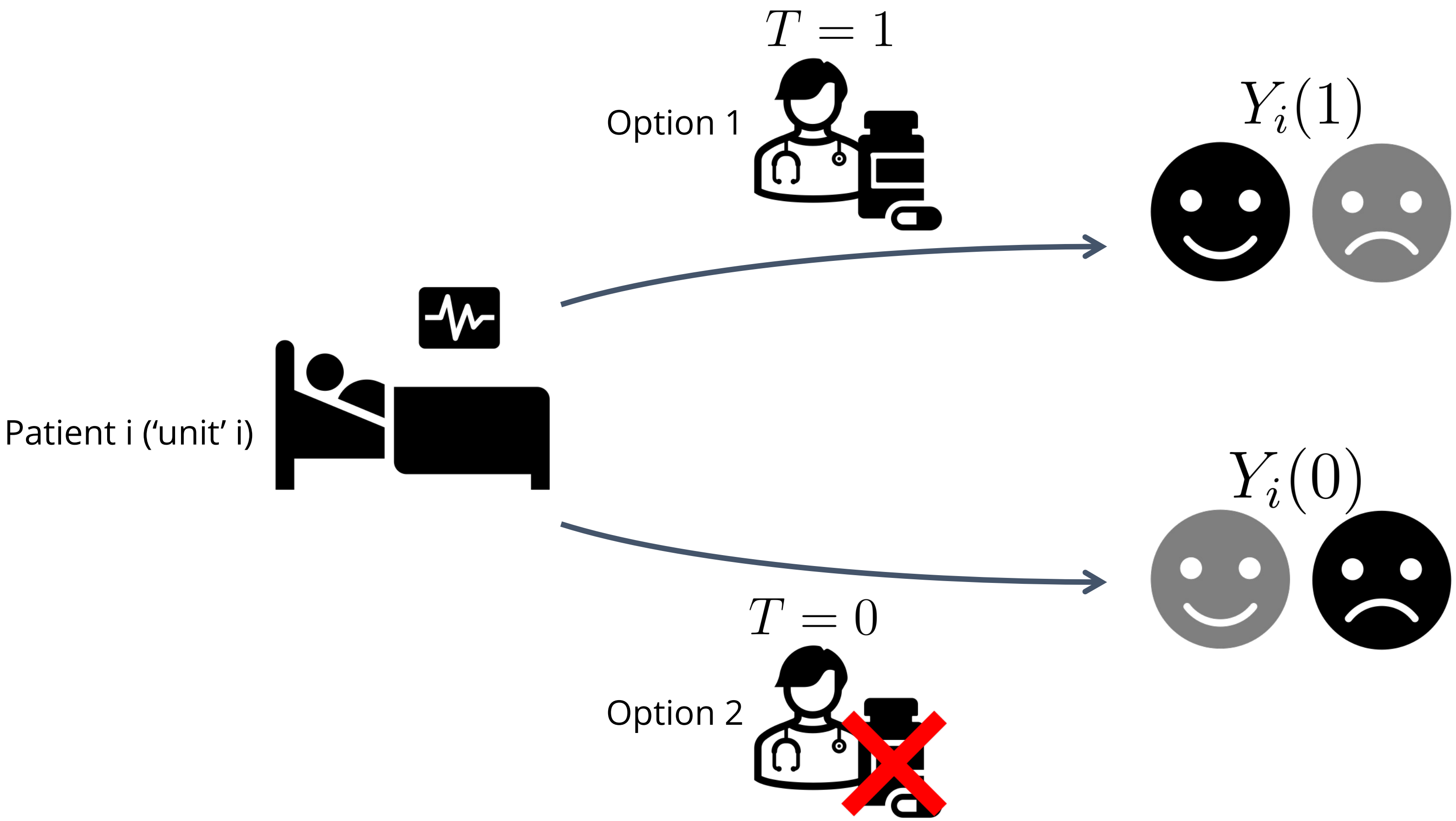
- Potential outcomes: Possible outcome of a treatment
- Example scenario: Administering a drug to cure a patient



Why does causal inference matter?

Confounders, Potential outcomes, Individual Treatment Effect (ITE)

- Example scenario: Administering a drug to cure a patient



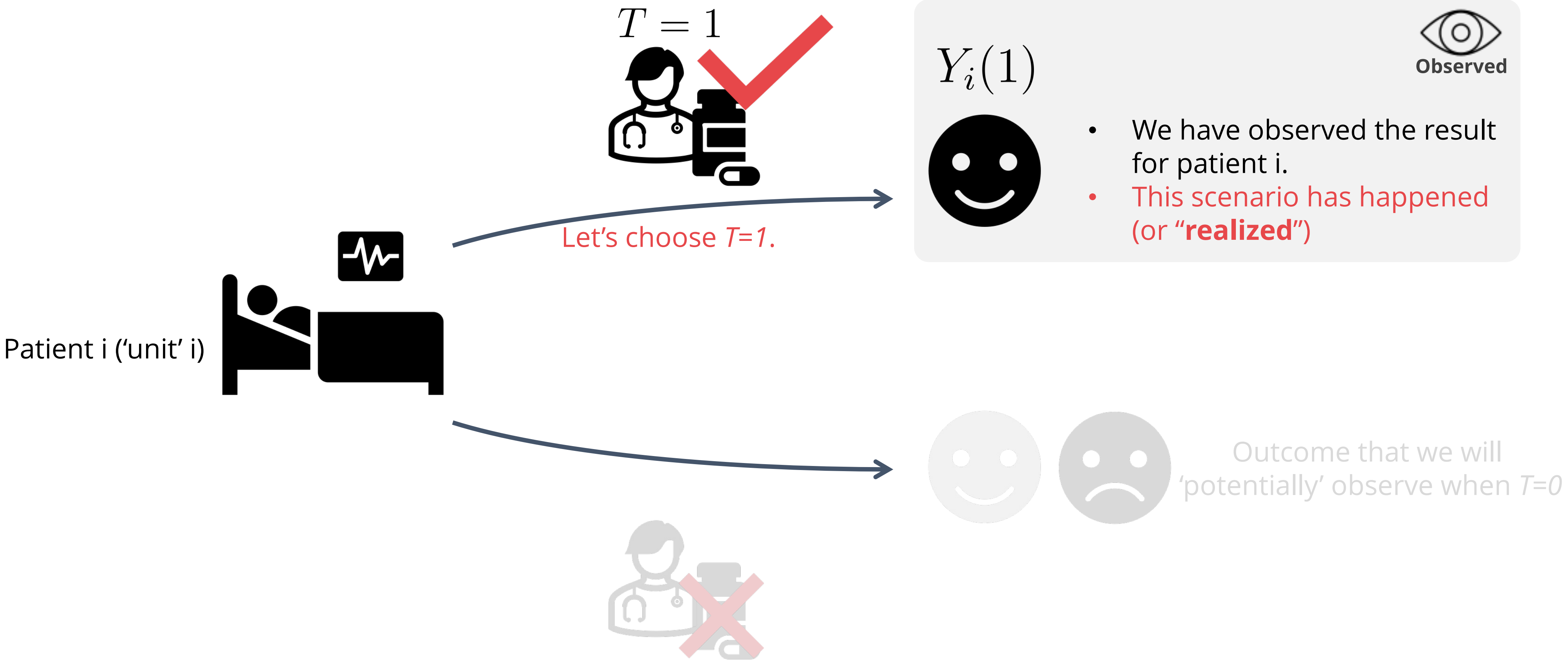
$$\tau_i = Y_i(1) - Y_i(0)$$

- **Q: What is the causal effect of the drug for unit i?**
- We woule like to observe the *individual treatment effect (ITE)* τ_i.
- This measures the causal effect, and we can use other forms beside subtractions (e.g., ratios)

The fundamental problem of causal inference

Factuals & Counterfactuals

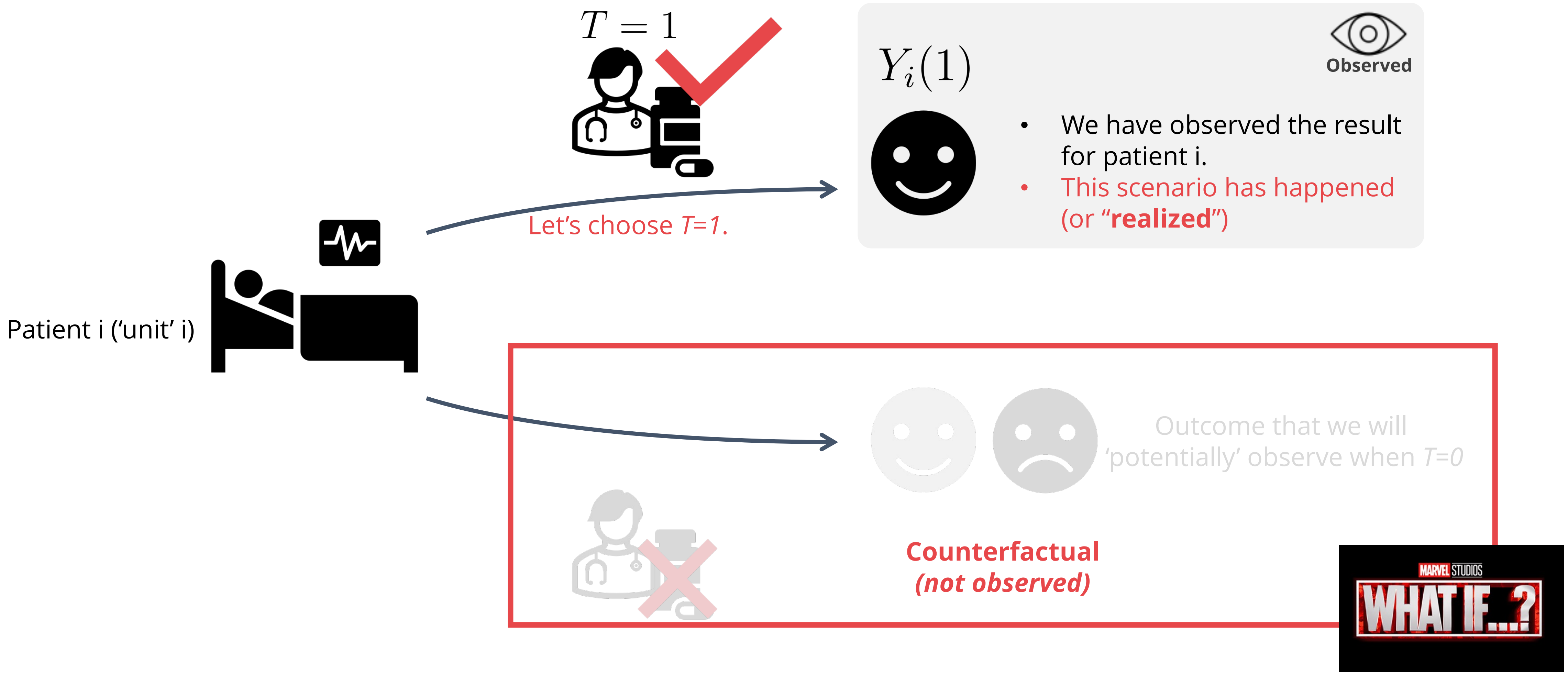
- Potential outcome: The **“potential”** part refers to the idea that **only one outcome is realized** after the intervention (decision to prescribe the drug to unit i)
- Before the intervention, there were two potential outcomes. **Only one** is realized after the action is conducted



The fundamental problem of causal inference

Factuals & Counterfactuals

- The observed timeline is a '**factual**', and the other potential scenario (which we will never know unless we develop a time machine) is '**counterfactual**'.
- Counterfactuals can also be described as '**what if? scenarios**'
- **Fundamental problem of causal inference: We do not observe all potential outcomes, just one.**



The fundamental problem of causal inference

Getting around the fundamental problem of causal inference

- Can we still calculate ITE?
- Or can we at least calculate the average ITEs over the units? = **Average Treatment Effect (ATE)**

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

- **Can we calculate this causal quantity via an equivalent statistical quantity?**
- Maybe just take the associational difference?:

$$\begin{aligned} \tau &= \mathbb{E}[Y(1) - Y(0)] \\ &= \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \quad \textit{(linearity of expectation)} \\ &= \mathbb{E}[Y(1)|T=1] - \mathbb{E}[Y(0)|T=0] \end{aligned}$$

Is this possible?
Sadly, this is generally not the case.
(Correlation is not causation)

The fundamental problem of causal inference

Getting around the fundamental problem of causal inference

Counterfactuals

Fundamental problem of causal inference

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	?	?

$$\mathbb{E}[Y(1)|T=1] \stackrel{?}{=} \mathbb{E}[Y(1)]$$

Table: Example dataset for drug administration.

- The table shows that the fundamental problem of causal inference can be seen as a missing data problem.
- **Q: What assumption is required such that just taking the Y(1) column and ignoring the missing data points is enough?**
- It only makes sense that the *T=1* subpopulation represents the whole population.
  - = The treatment group should not be biasedly selected in any way.
  - = The treatment is completely randomized
  - = **Randomized Control Trials (RCTs)**
  - = $\mathbb{E}[Y(1)|T=1] = \mathbb{E}[Y(1)|T=0]$ and vice versa.

The fundamental problem of causal inference

Getting around the fundamental problem of causal inference

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	?	?

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

Table: Example dataset for drug administration.

Ignorability / Exchangability assumption

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

*The **assignment of the treatment** to individual units must be **independent of potential outcomes** (completely random).*

→ This makes the control group a very good proxy of what would have happened to the treated group if they had not received the treatment (= counterfactual).

$$\tau = \mathbb{E}[Y(1) - Y(0)]$$ *Causal relation*

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

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

= Average treatment effect on the treatement group (T=1) — $\mathbb{E}[Y(1)|T=1] - \mathbb{E}[Y(0)|T=1]$

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

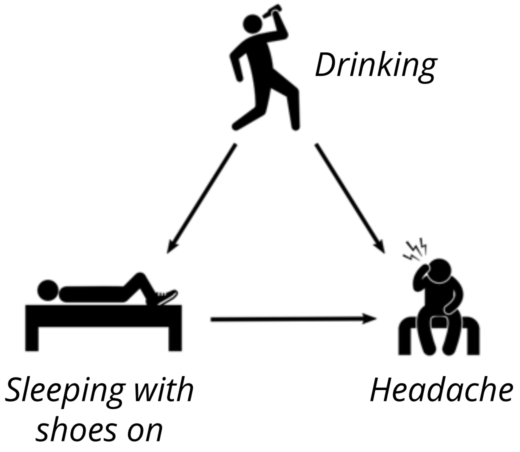
The ignorability assumption makes this sufficient to represent the whole population

We want this to be zero, which is assured by the ignorability assumption

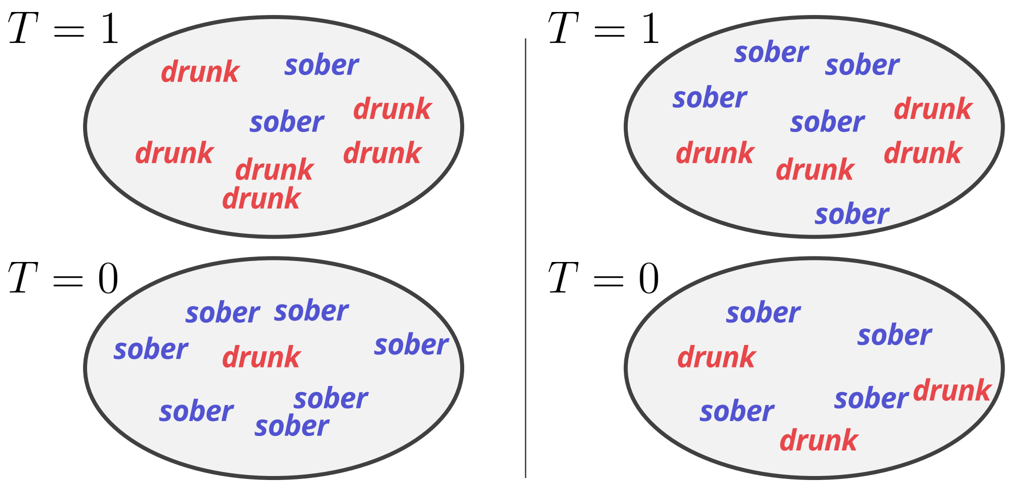
The fundamental problem of causal inference

Getting around the fundamental problem of causal inference

Revisiting the drinking example…



T=1: Sleep with shoes on / *T=0*: Sleep without shoes



High selection bias
(not a fair comparison)

No selection bias
(fair comparison)

Ignorability / Exchangability assumption

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$$\tau = \mathbb{E}[Y(1) - Y(0)]$$ *Causal relation*

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

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

$$= \underbrace{\mathbb{E}[Y(1)|T=1] - \mathbb{E}[Y(0)|T=1]}_{\text{Average treatment effect on the treatement group } (T=1)} + \underbrace{\mathbb{E}[Y(0)|T=1] - \mathbb{E}[Y(0)|T=0]}_{\text{Selection bias}}$$

= Average treatment effect on the treatement group (T=1)

The ignorability assumption makes this sufficient to represent the whole population

= Selection bias

We want this to be zero, which is assured by the ignorability assumption

The fundamental problem of causal inference

The flowchart of causal inference

Causal Model

↓ *Use directed acyclic graphs (DAGs)*

Causal Estimand

↓ *Identification*

Statistical Estimand

↓ *Estimation* — *Use various statistical tools*

Estimate

Ignorability / Exchangability assumption

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

*The **assignment of the treatment** to individual units must be **independent of potential outcomes** (completely random).*

→ This makes the <u>control group a very good proxy</u> of what would have happened to the treated group if they had not received the treatment (= <u>counterfactual</u>).

Takeaway messages & Further questions

- *Causal structure is a framework for a deeper understanding of the underlying problem*
- ***Correlation does not imply Causation**, therefore we need to **identify** the causal estimand.*
- ***Fundamental problem of causal inference**: How do we get information from the **counterfactual**?*
- ***Randomized selection of the treatment group (RCTs)** is a great way to get around the fundamental problem of causal inference.*

- *Are there **other ways** to get around the fundamental problem of causal inference?*
- *How can we utilize this framework in **machine learning / deep learning research**?*

Thank you!