Making Policy with Data

An Introductory Course on Policy Evaluation

Lecture 2. Causation

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Take-aways

1. Correlation ≠ causation
2. Always ask: what may the “counterfactual” look like?
3. No causation without manipulation

Correlation is NOT causation.

Correlation ≠ Causation

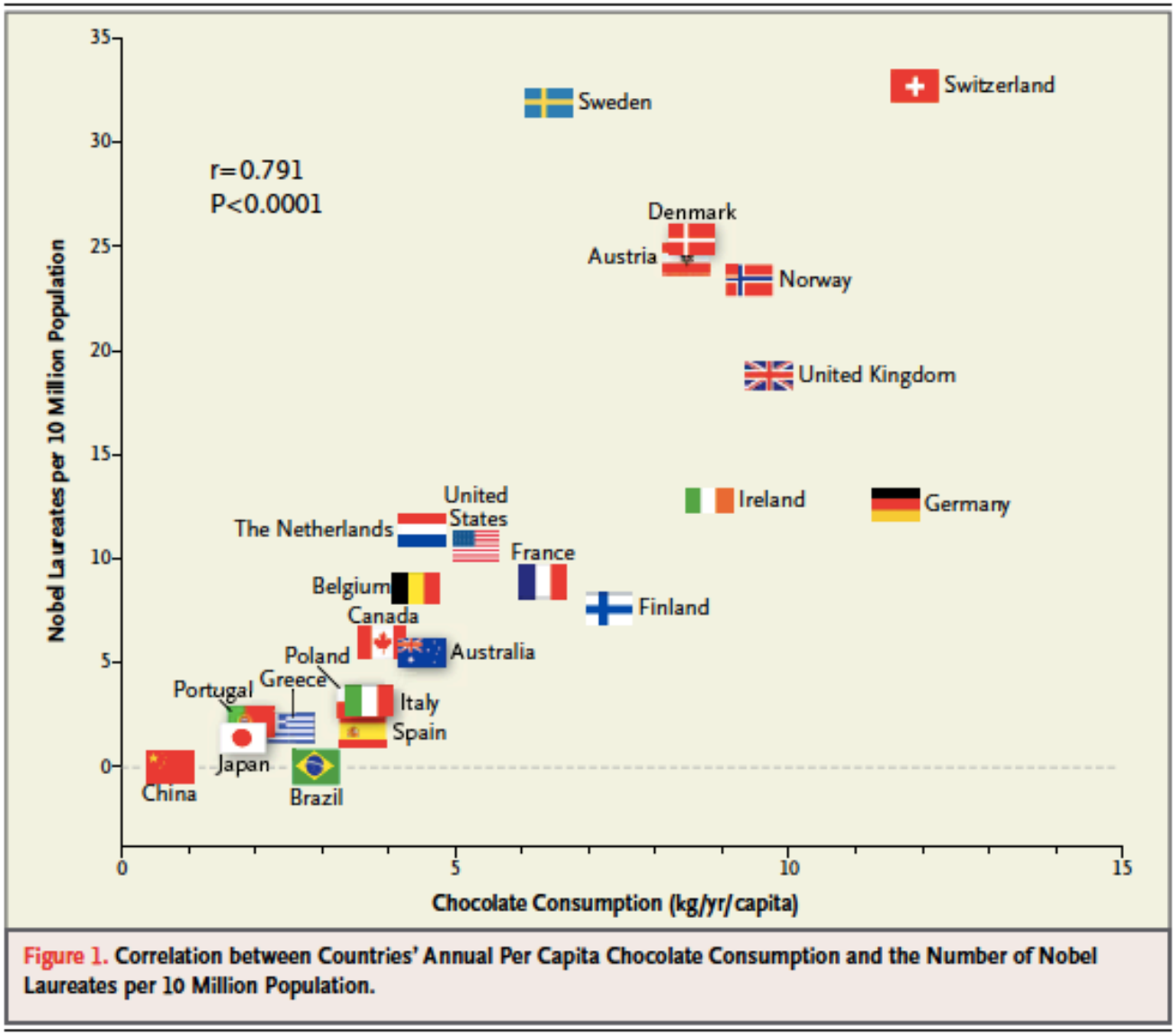
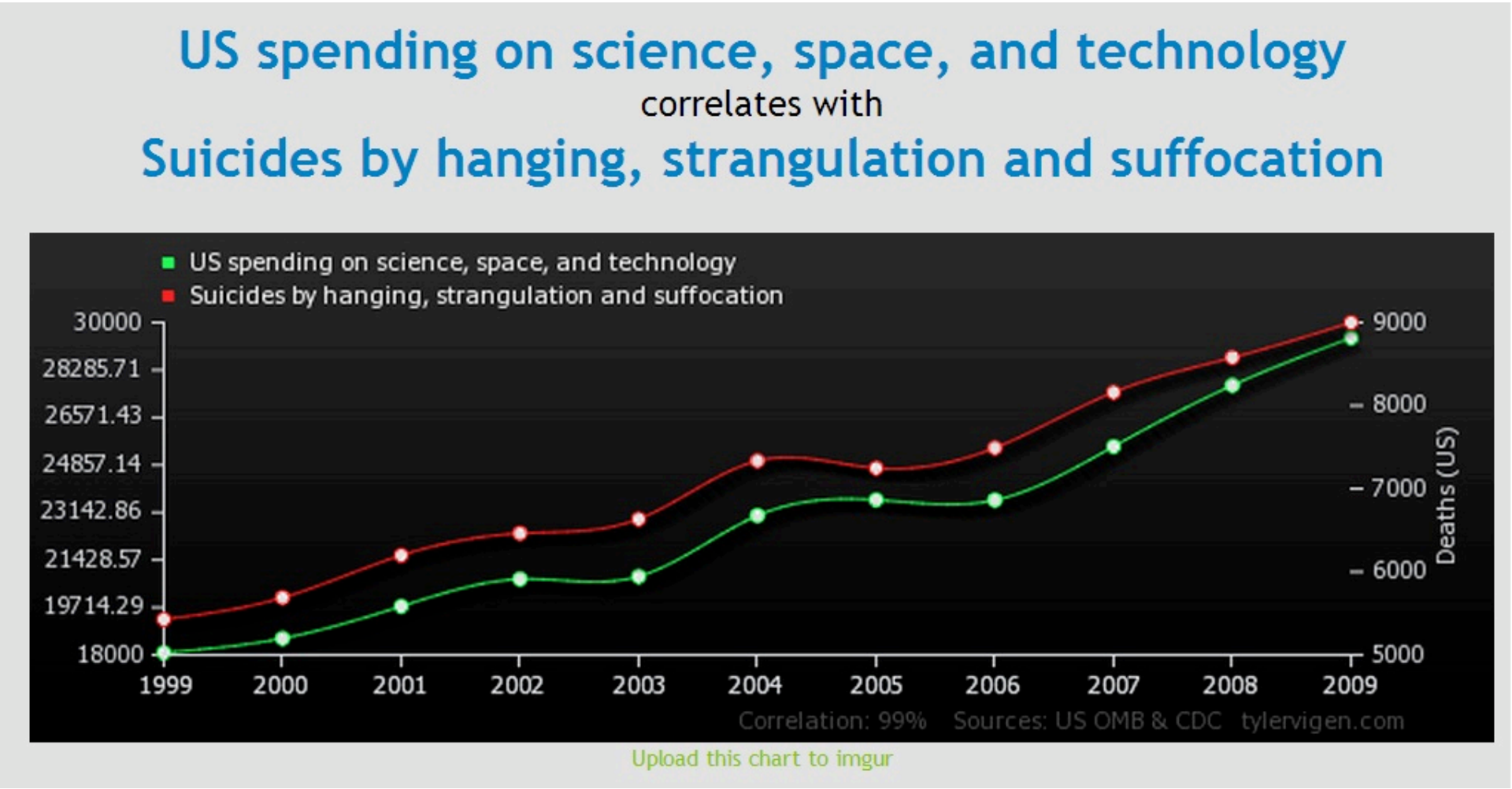
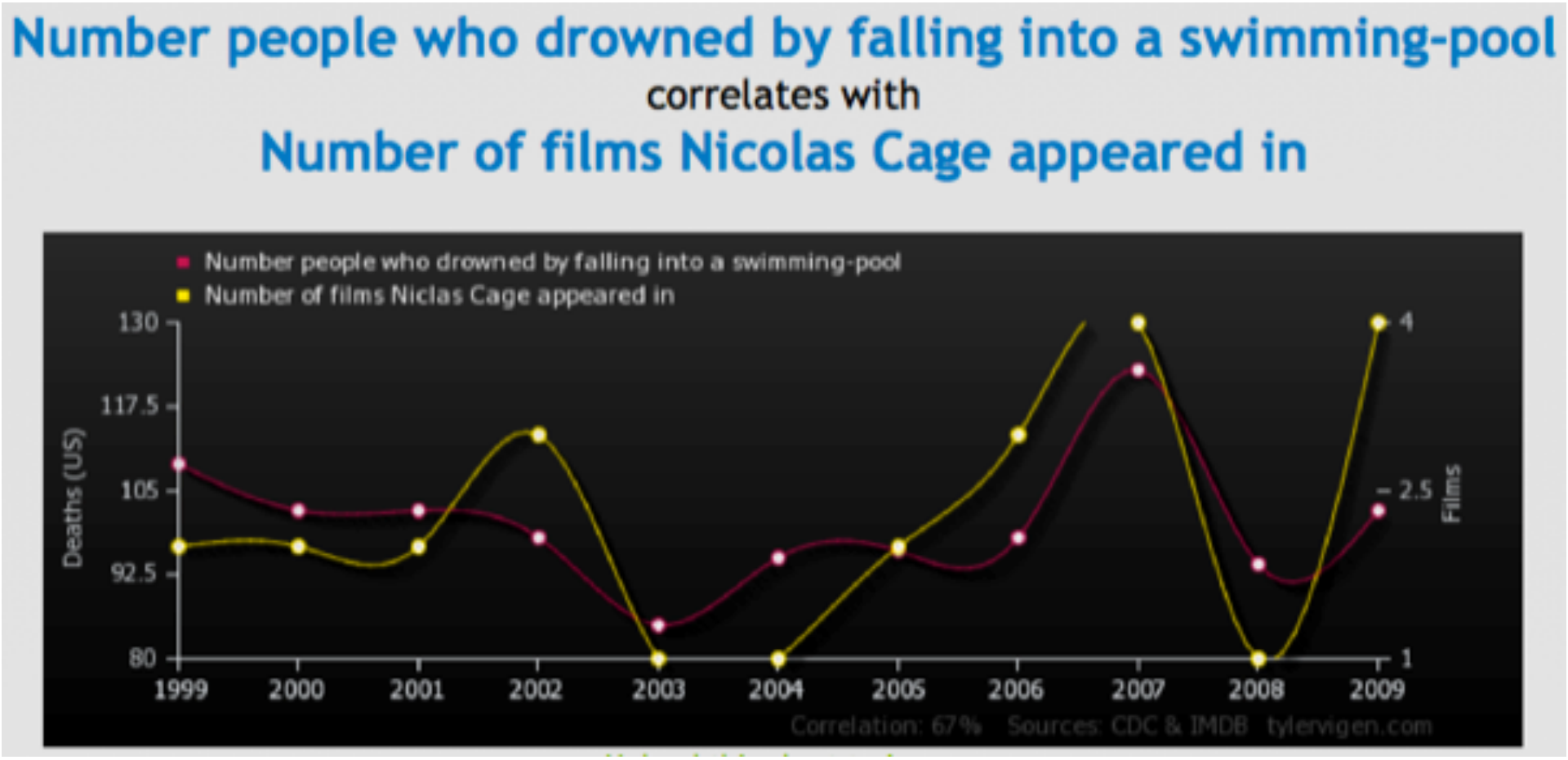


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

Correlation ≠ Causation



Correlation ≠ Causation



Correlation ≠ Causation

ZOO ANIMALS

Dogs Walked by Men Are More Aggressive

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Male dogs are more likely to smell female dogs while on walks. ISTOCKPHOTO



DNEWSvid



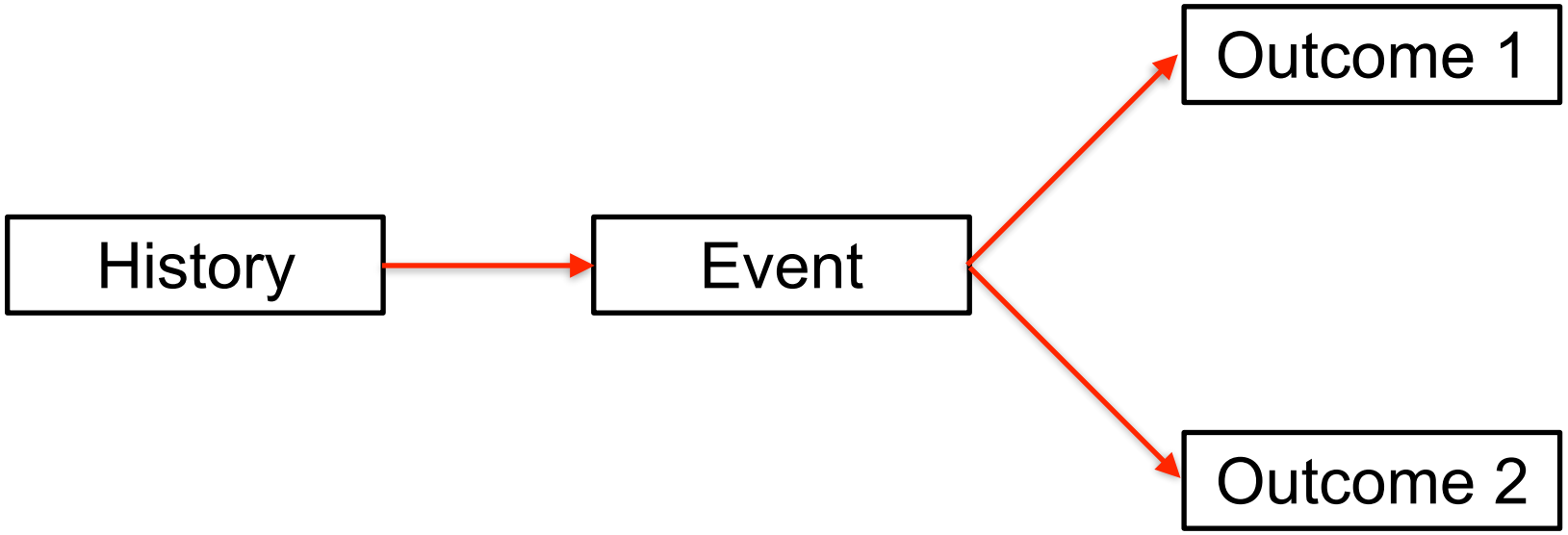
Correlation ≠ Causation

- The problem with correlations for causal inference is that they often arise for reasons that have nothing to with the causal process under investigation (spurious correlation)
- Correlations are often driven by selection effects:
    - It's not that men make dogs more aggressive, but men might simply prefer more aggressive dogs.
    - Basketball players are tall, but does playing basketball make you taller?
- Correlations are often driven by confounding factors: ice cream consumption is highly correlated with drowning, but that doesn't mean that eating ice cream causes drowning
- Correlations are neither a necessary nor sufficient condition for causality

Counterfactual

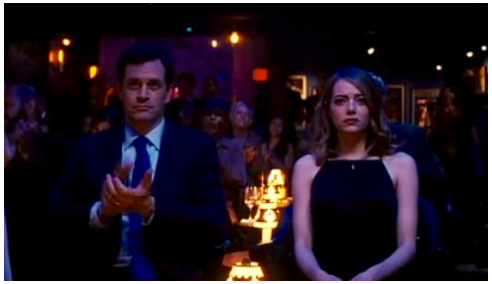
What would happen if … ?

Counterfactuals



Parallel Universe!

Counterfactuals



Actual

History → Event → Actual / Counterfactual



Counterfactual



Counterfactuals



Actual

History



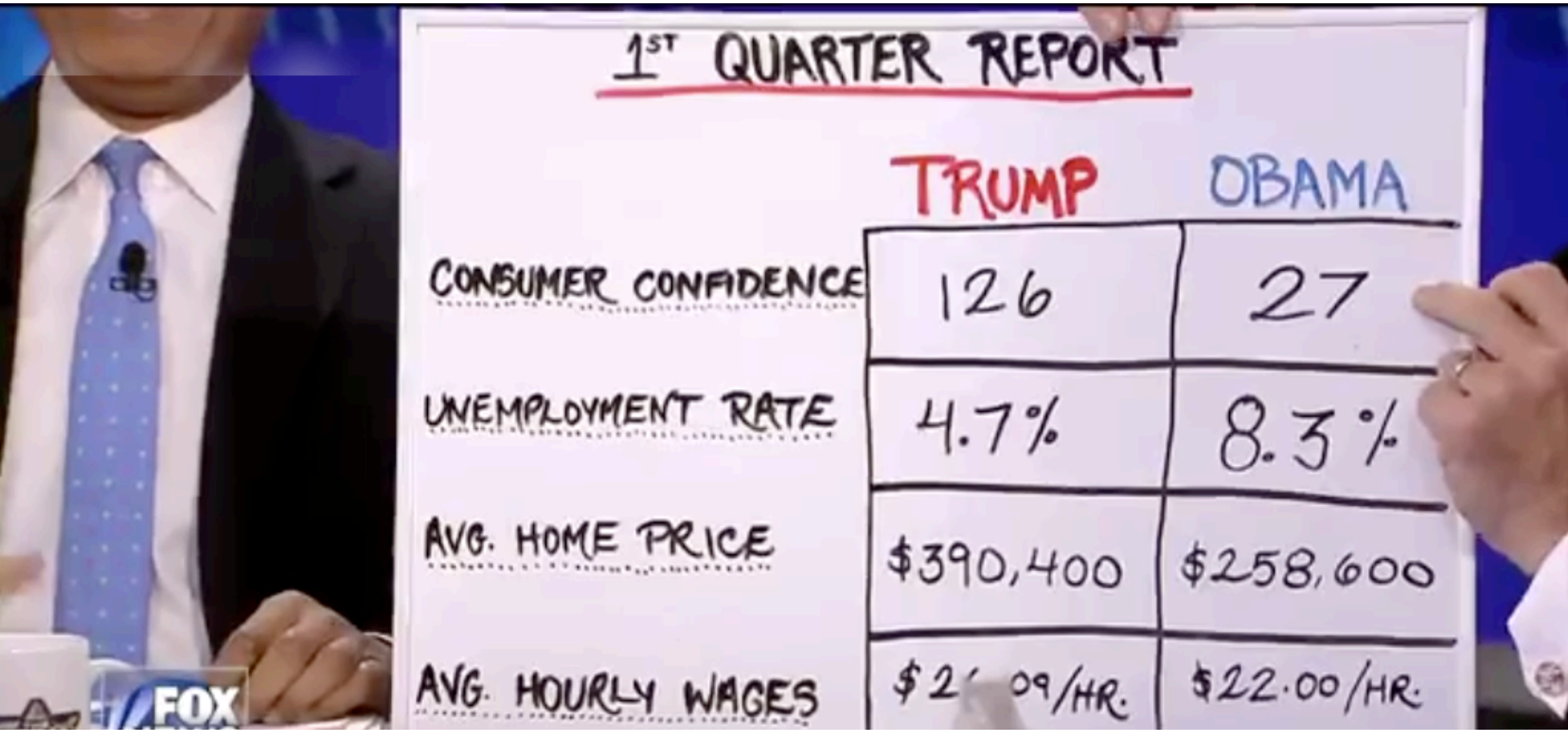
Event



Counterfactual

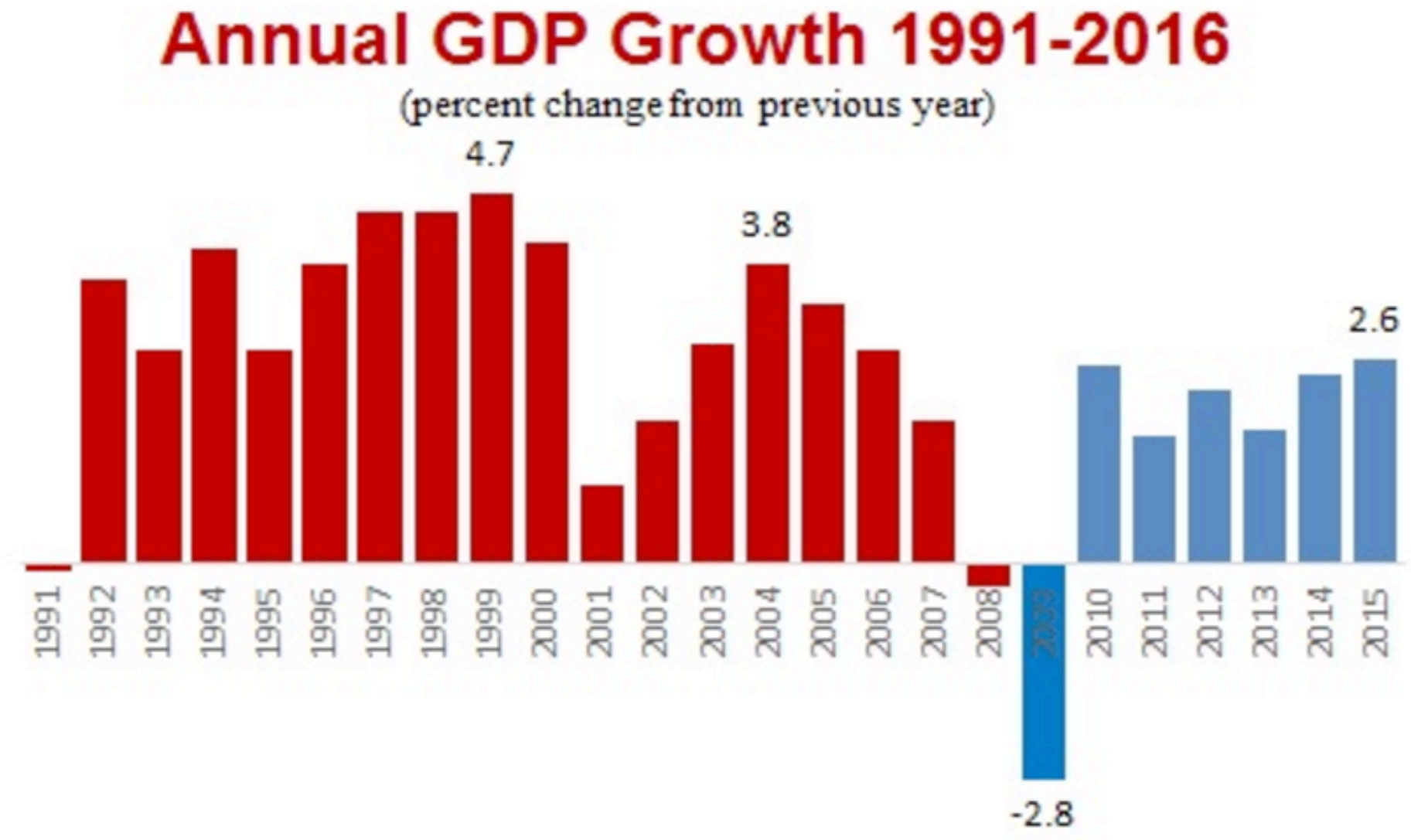


Why Are Counterfactuals Important?



Source

Why Are Counterfactuals Important?



Causality

Difference between the actual and counterfactual.

Neyman-Rubin Model

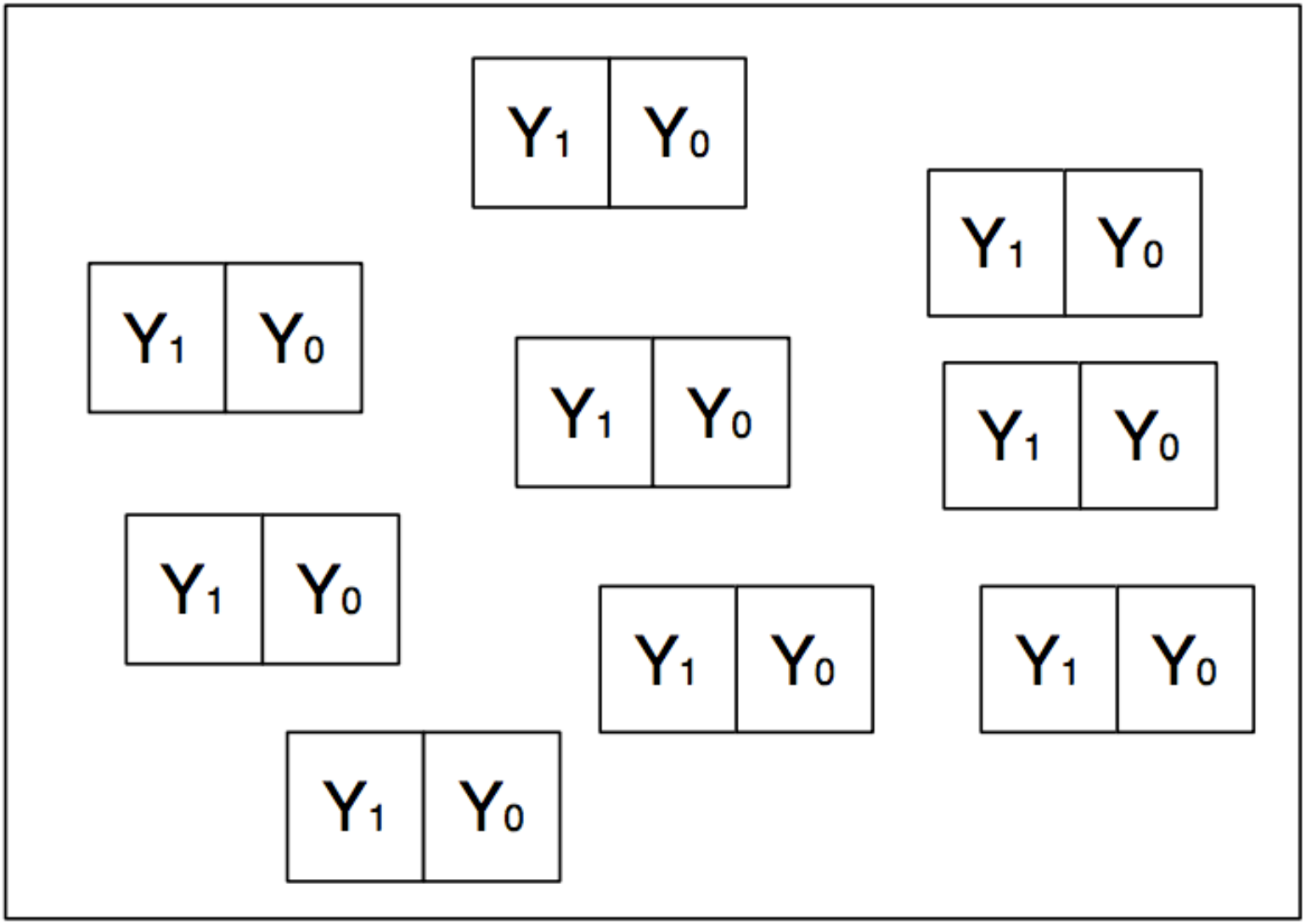


Jerzy Neyman

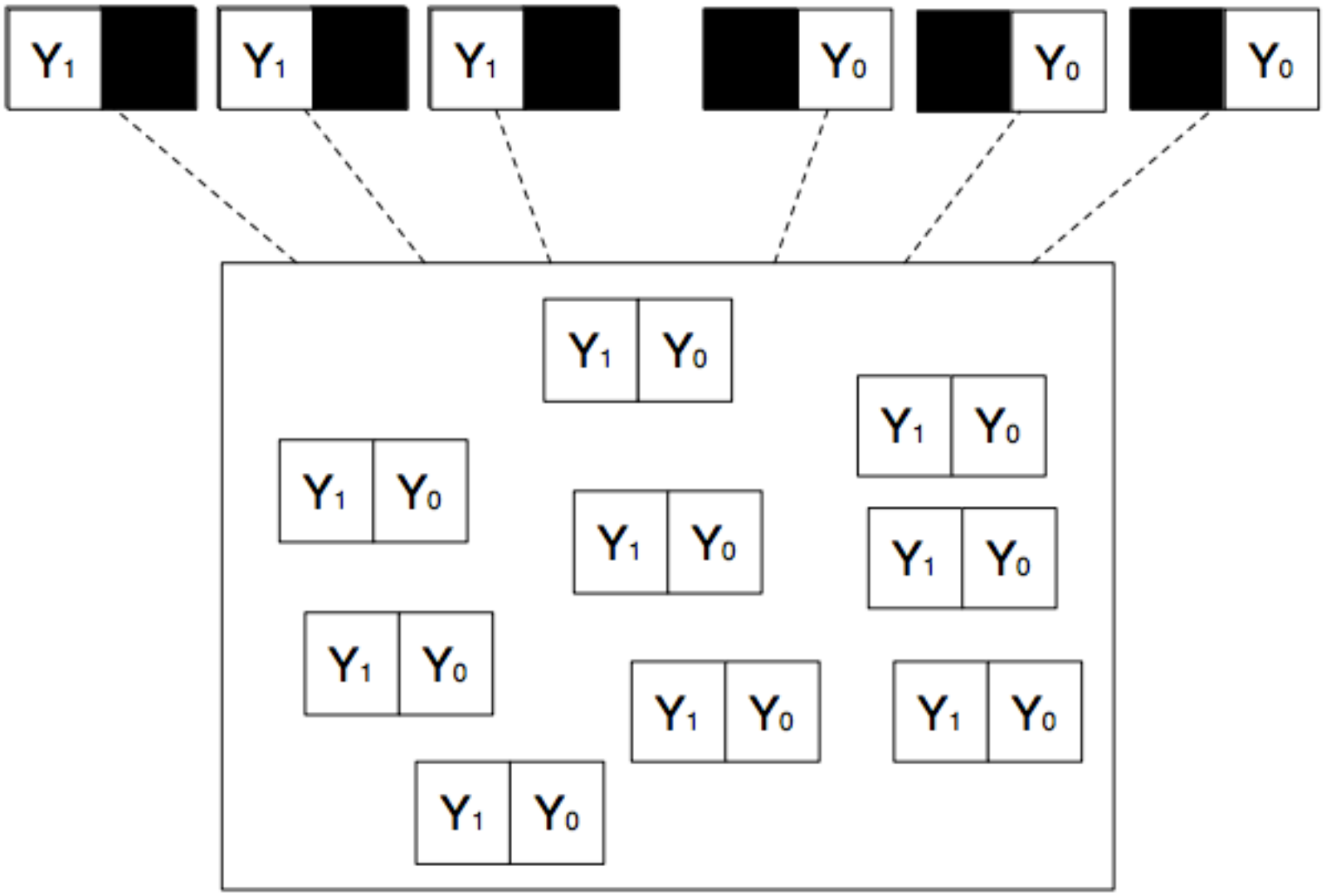


Donald Rubin

Neyman-Rubin Potential Outcome Model



Neyman-Rubin Model



Causality with Potential Outcomes

Definition (Treatment)

D_i: Indicator of treatment intake for *unit i*

$$D_i = \begin{cases} 1 & \text{if unit } i \text{ received the treatment} \\ 0 & \text{otherwise.} \end{cases}$$

Definition (Outcome)

Y_i: Observed outcome variable of interest for unit i. The treatment occurs temporally before the outcomes.

Definition (Potential Outcome)

Y_{0i} and Y_{1i}: Potential outcomes for unit i

$$Y_{di} = \begin{cases} Y_{1i} & \text{Potential outcome for unit } i \text{ with treatment} \\ Y_{0i} & \text{Potential outcome for unit } i \text{ without treatment} \end{cases}$$

Causality with Potential Outcomes

Definition (Causal Effect)

Causal effect of the treatment on the outcome for unit i is the difference between its two potential outcomes:

$$\alpha_i = Y_{1i} - Y_{0i}$$

Assumption

Observed outcomes are realized as

$$Y_i = D_i \cdot Y_{1i} + (1 - D_i) \cdot Y_{0i} \text{ so } Y_i = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases}$$

Definition (Fundamental Problem of Causal Inference)

Cannot observe both potential outcomes (Y_{1i}, Y_{0i})

Causal Effect





Trump = 1

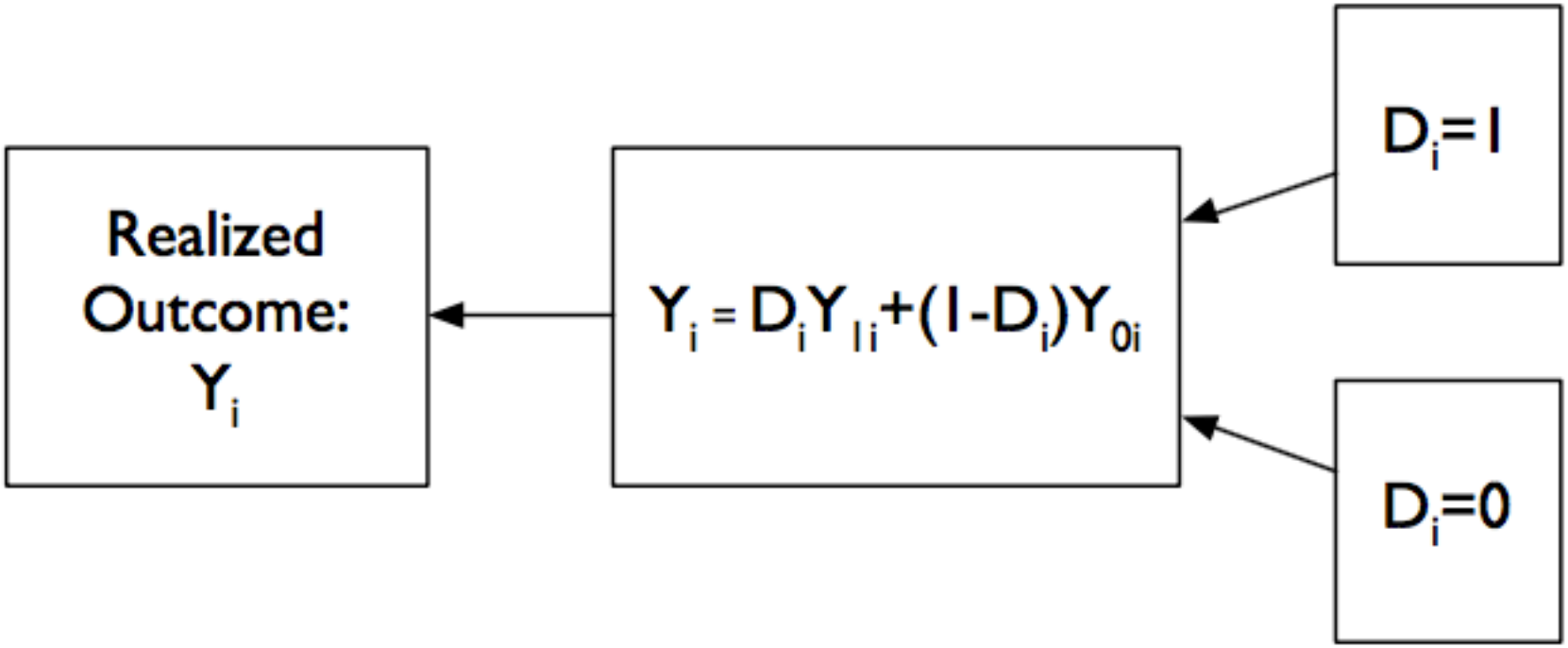


Difference?

Trump = 0



Causal Effect



Problem: We do not observe the counterfactuals!

Fundamental Problem of Causal Inference

1. We can never observe both Y_{1i} and Y_{0i} *simultaneously*

2. As a result, we can never know causal effect with certainty

i	Y_{1i}	Y_{0i}	Y_i	D_i	$Y_{1i} - Y_{0i}$
1	3	0	3	1	3
2	1	1	1	1	0
3	1	0	0	0	1
4	1	1	1	0	0

Ideally: Two Version of the Same Person

Treatment

Drug





I'm Tom

Placebo





I'm Clone Tom

Best Solution: Randomized Trails

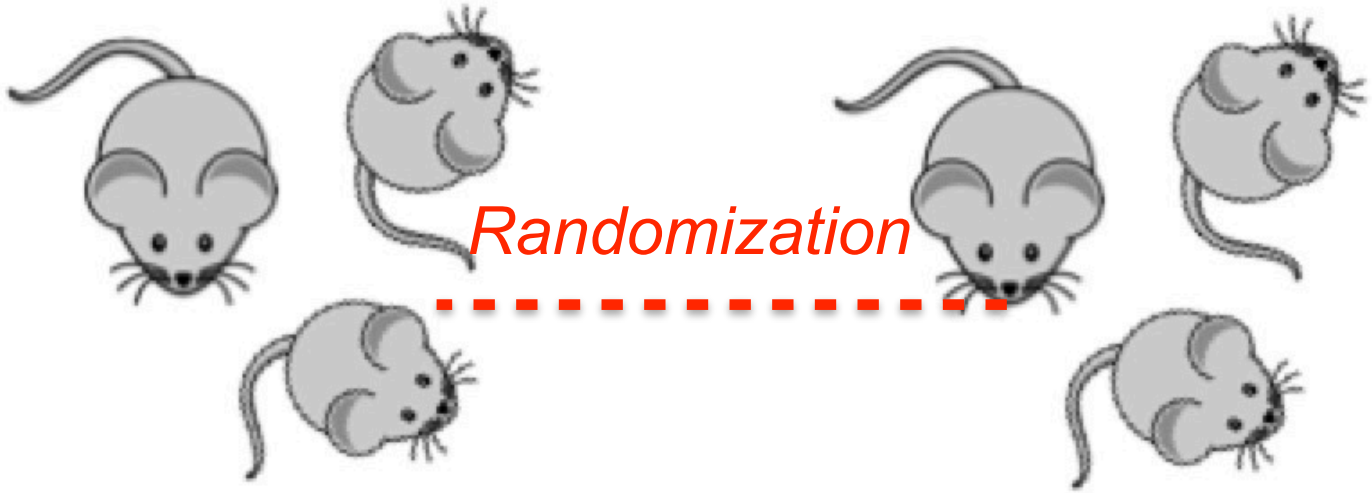
Drug

Placebo

Treatment







Group A

Group B

Best Solution: Randomized Trails

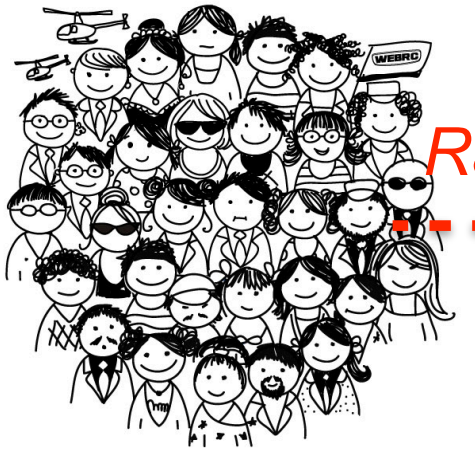
Drug

Placebo

Treatment







Randomization



Group A

Group B

Target (Estimand)

Because individual treatment effects are unobservable, we shift our interest to the Average Treatment Effect (ATE)

Definition (ATE)

Average Treatment Effect (ATE) parameter:

Average of all treatment potential outcomes − Average of all control potential outcomes

or

$$\alpha_{ATE} = \frac{\sum_i^N Y_{1i}}{N} - \frac{\sum_i^N Y_{0i}}{N}$$

or

$$\alpha_{ATE} = \mathbf{E}[Y_{1i} - Y_{0i}]$$

Average Treatment Effect (ATE)

Imagine a study population with 4 units:

i	$\Pr(D_i = 1)$	D_i	Y_{1i}	Y_{0i}	$Y_{1i} - Y_{0i}$
1	?	1	10	4	6
2	?	1	1	2	-1
3	?	0	3	3	0
4	?	0	5	2	3

What is the ATE?

$$\mathbf{E}[Y_{1i} - Y_{0i}] = 1/4 \times (6 + -1 + 0 + 3) = 2$$

Note: Average effect is positive, but α_i are negative for some units!

Other Estimands

Definition (ATT)

Average treatment effect on the treated is:

$$\alpha_{ATT} = \mathbf{E}[Y_{1i} - Y_{0i}|D_i = 1]$$

Definition (ATC)

Average treatment effect on the controls is:

$$\alpha_{ATT} = \mathbf{E}[Y_{1i} - Y_{0i}|D_i = 0]$$

Average Treatment Effect on the Treated (ATT)

Imagine a study population with 4 units:

i	$\Pr(D_i = 1)$	D_i	Y_{1i}	Y_{0i}	$Y_{1i} - Y_{0i}$
1	?	1	10	4	6
2	?	1	1	2	-1
3	?	0	3	3	0
4	?	0	5	2	3

What is the ATT and ATC?

$$\mathbf{E}[Y_{1i} - Y_{0i} | D_i = 1] = 1/2 \times (6 + -1) = 2.5$$
$$\mathbf{E}[Y_{1i} - Y_{0i} | D_i = 0] = 1/2 \times (0 + 3) = 1.5$$

Selection Bias

Naive comparison is often misleading

Review of Key Concepts

- Potential Outcome Model
- Counterfactual
- Causal effect
- Causal estimands: ATE, ATT, ATC
- Treatment assignment

Naive Comparison: Difference in Means

- Comparisons between observed outcomes of treated and control units can often be misleading term unlikely to be 0 in most applications

$$
\begin{aligned}
&E[Y_i|D=1] - E[Y_i|D_i=0] \\
&\qquad = E[Y_{1i}|D_i=1] - E[Y_{0i}|D_i=0] \\
&\qquad = \underbrace{E[Y_{1i} - Y_{0i}|D_i=1]}_{\text{ATT}} + \underbrace{\{E[Y_{i0}|D_i=1] - E[Y_{0i}|D_i=0]\}}_{\text{BIAS}}
\end{aligned}
$$

- Bias term unlikely to be 0 in most applications
- Selection into treatment is often associated with the potential outcomes.

Selection Bias

$$
\begin{aligned}
E[Y_i|D=1] - E[Y_i|D_i=0] & \\
&= E[Y_{1i}|D_i=1] - E[Y_{0i}|D_i=0] \\
&= \underbrace{E[Y_{1i} - Y_{0i}|D_i=1]}_{\text{ATT}} + \underbrace{\{E[Y_{i0}|D_i=1] - E[Y_{0i}|D_i=0]\}}_{\text{BIAS}}
\end{aligned}
$$

- **Essentially, bad comparison group**
- Example
  - Schooling and income
  - Chocolate consumption and Nobel Prizes

No Causation without Manipulation!

What's the ideal experiment?

Assignment Mechanism

- Since missing potential outcomes are unobservable we must make assumptions to fill them in, i.e. estimate missing potential outcomes.
- In the causal inference literature, we typically make assumptions about the assignment mechanism to do so.

Definition (Assignment Mechanism)

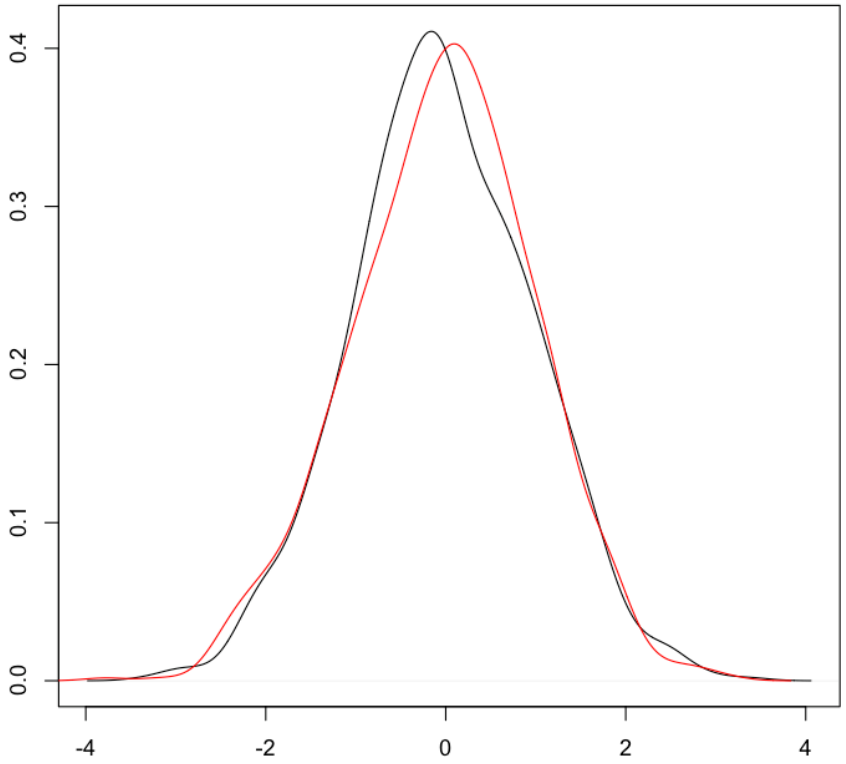
Assignment mechanism is the procedure that determines which units are selected for treatment. Examples include:

- random assignment
- selection on observables
- selection on unobservables

- Most statistical models of causal inference attain **identification of treatment effects** by restricting the assignment mechanism in some way.

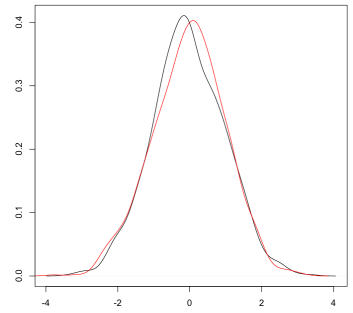
Manipulation

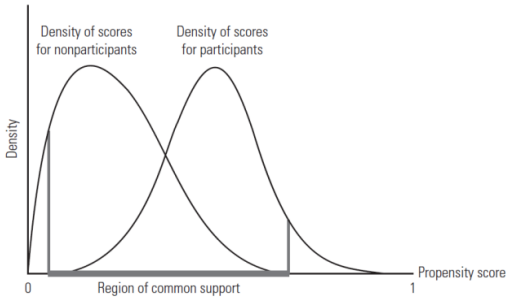
- Randomization is a type of manipulation
- It works because the treatment and control groups look very similar in ALL aspects!

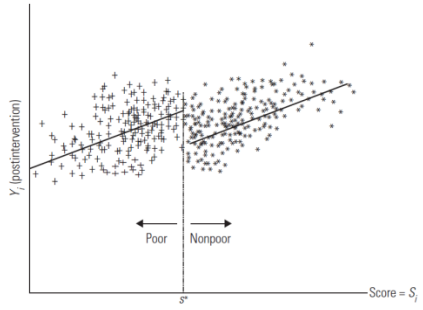


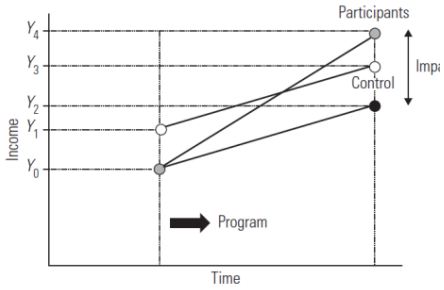
Methods of Approximating Counterfactuals

- Randomized Trials
- Matching
- Regression Discontinuity Design
- Difference-in-differences

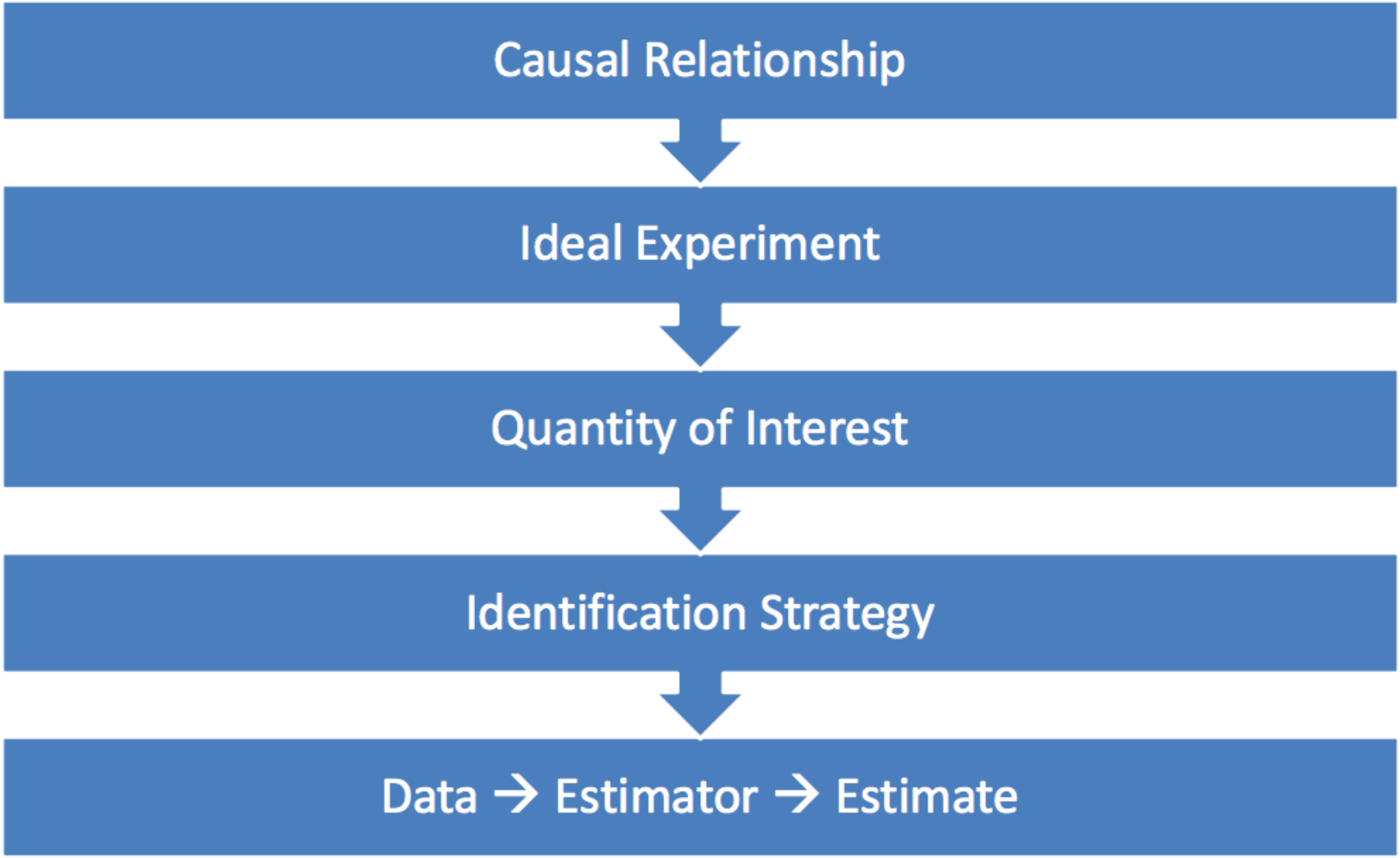








Causal Inference Workflow



Neyman-Rubin Causal Model

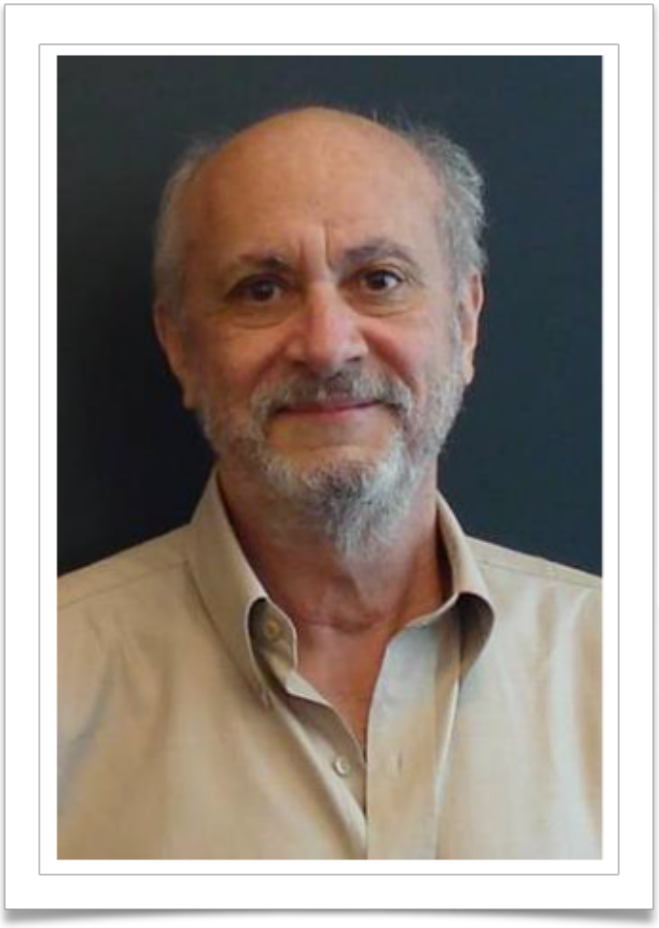
- Useful for studying the “effects of causes,” less so for the “causes of effects.”
- No assumption of homogeneity, allows for causal effects to vary unit by unit.
    - No single “causal effect,” thus the need to be precise about the target estimand.
- Distinguishes between observed outcomes and potential outcomes.
- Causal inference is a missing data problem: we typically make assumptions about the assignment mechanism to go from descriptive inference to causal inference.

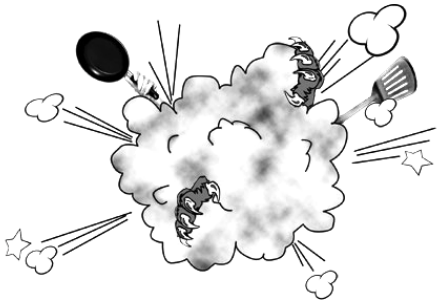
Alternative Causal Model (e.g. DAG by Judea Pearl)

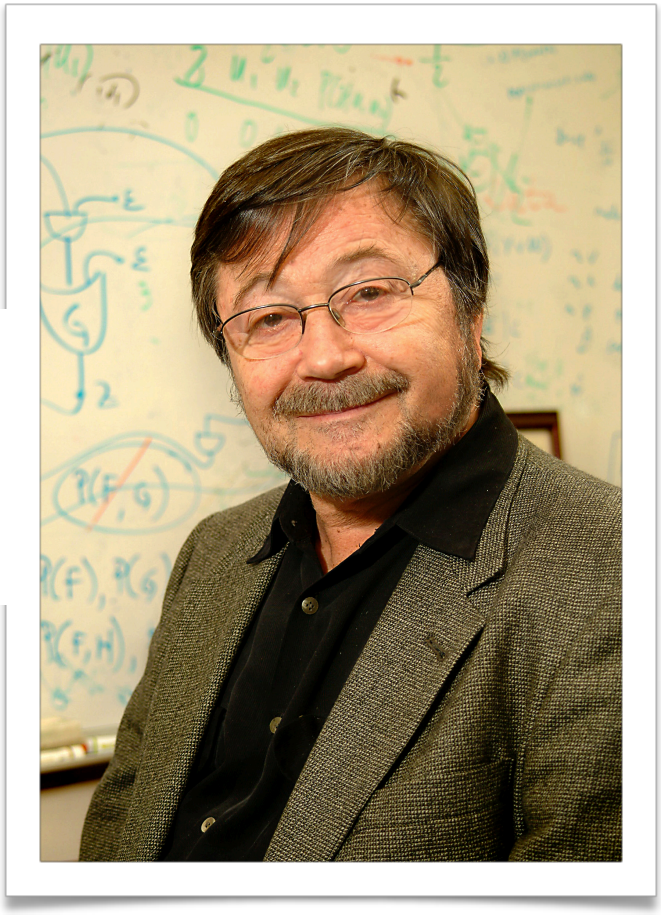


- Structural Equation Modeling:
  - Write down causal model using Directed Acyclic Graphs (DAG)
  - Causal effects are defined by interventions that set variables to specified values in the causal model.
  - Set of axioms ("Do Calculus") that establish identifiablity of causal parameters given structure of the causal graph.
  - Can be re-expressed in potential outcome notation (though sometimes difficult!)
- Causation without Counterfactuals (Dawid 2000)

Rubin vs. Pearl







Rubin:
No manipulation, no causation!

Pearl:
What's the mechanism?

Summary

1. Always ask:
   (1) What may the “counterfactual” look like?
   (2) What’s the ideal experiment?

2. Correlation ≠ causation often because of selection bias

3. No causation without manipulation

4. Effects of causes ≠ cause of effects