Book of Why, part 2

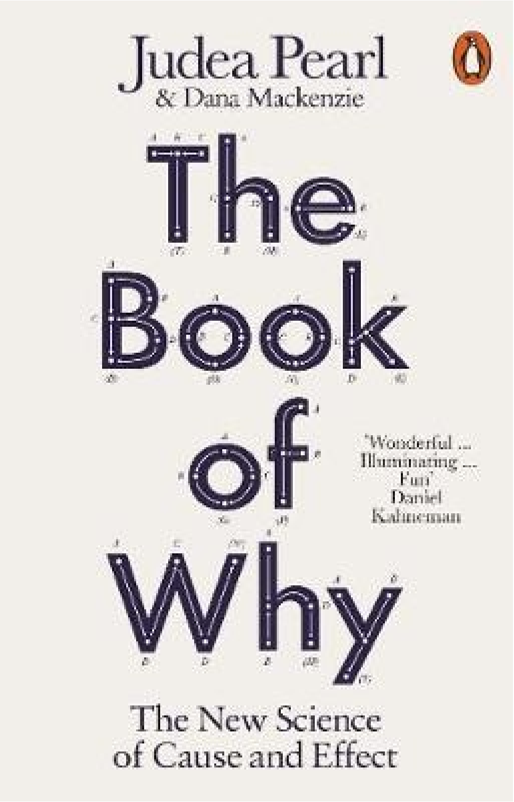


Image 5

Jasper Henze
Seminar: How to Lie with Statistics

Overview

- Paradoxes
- How to predict effects of interventions
- Counterfactuals
- Mediation

Berkson's Paradox

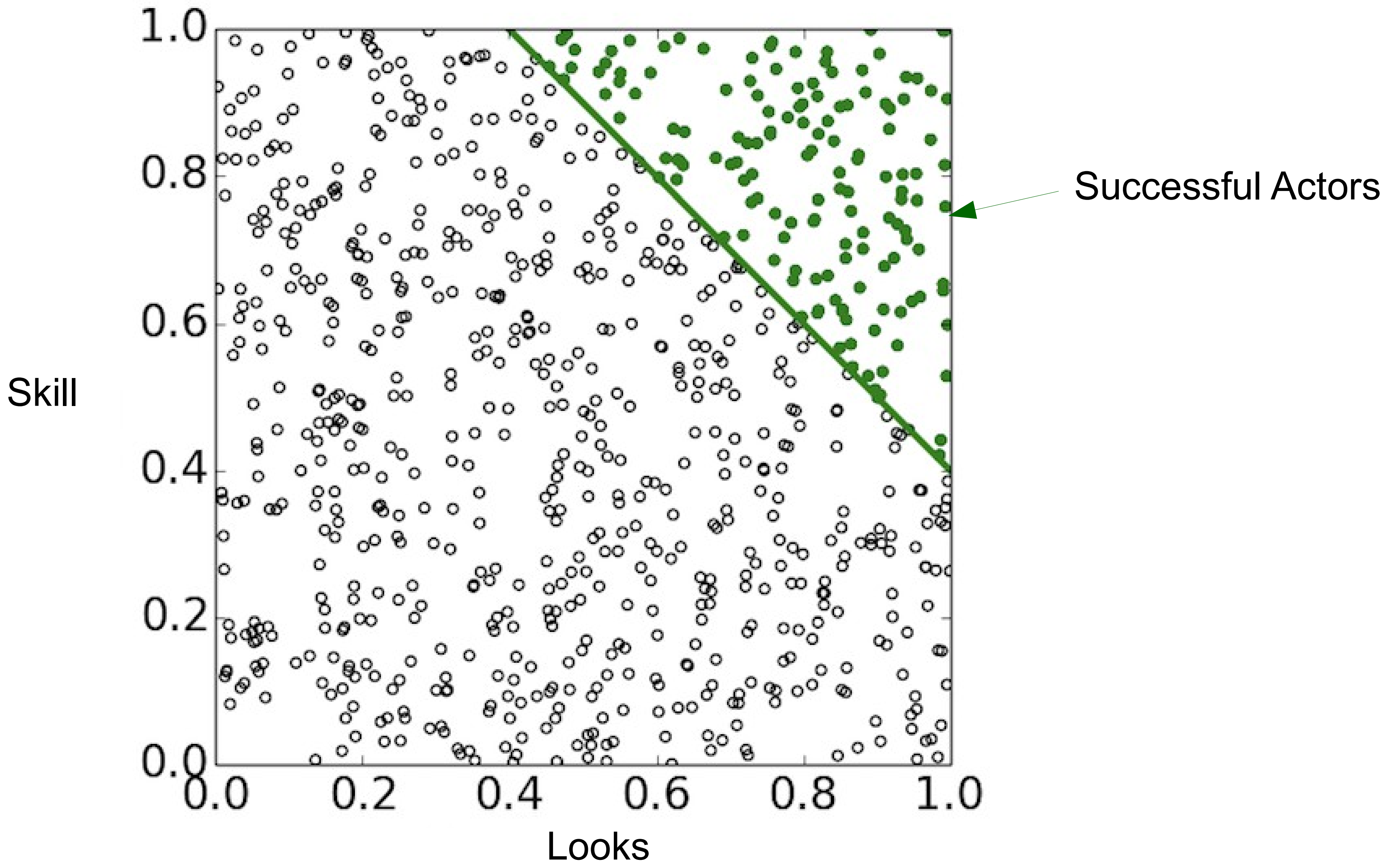
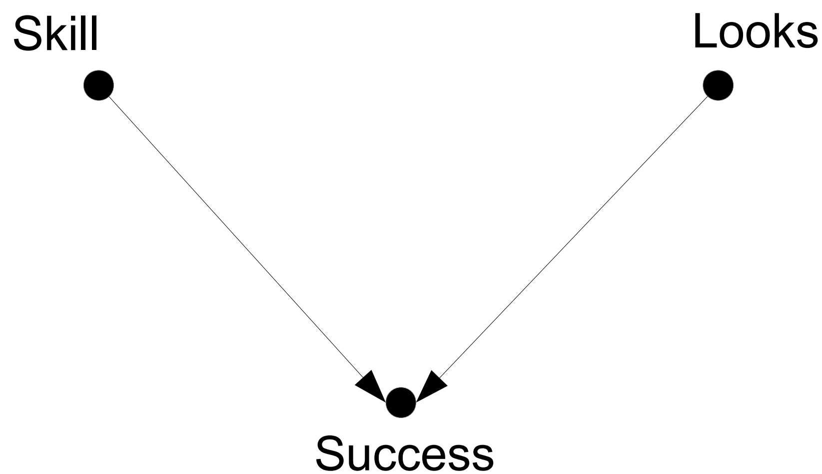


Image 1

Berkson's Paradox



Monty Hall Paradox

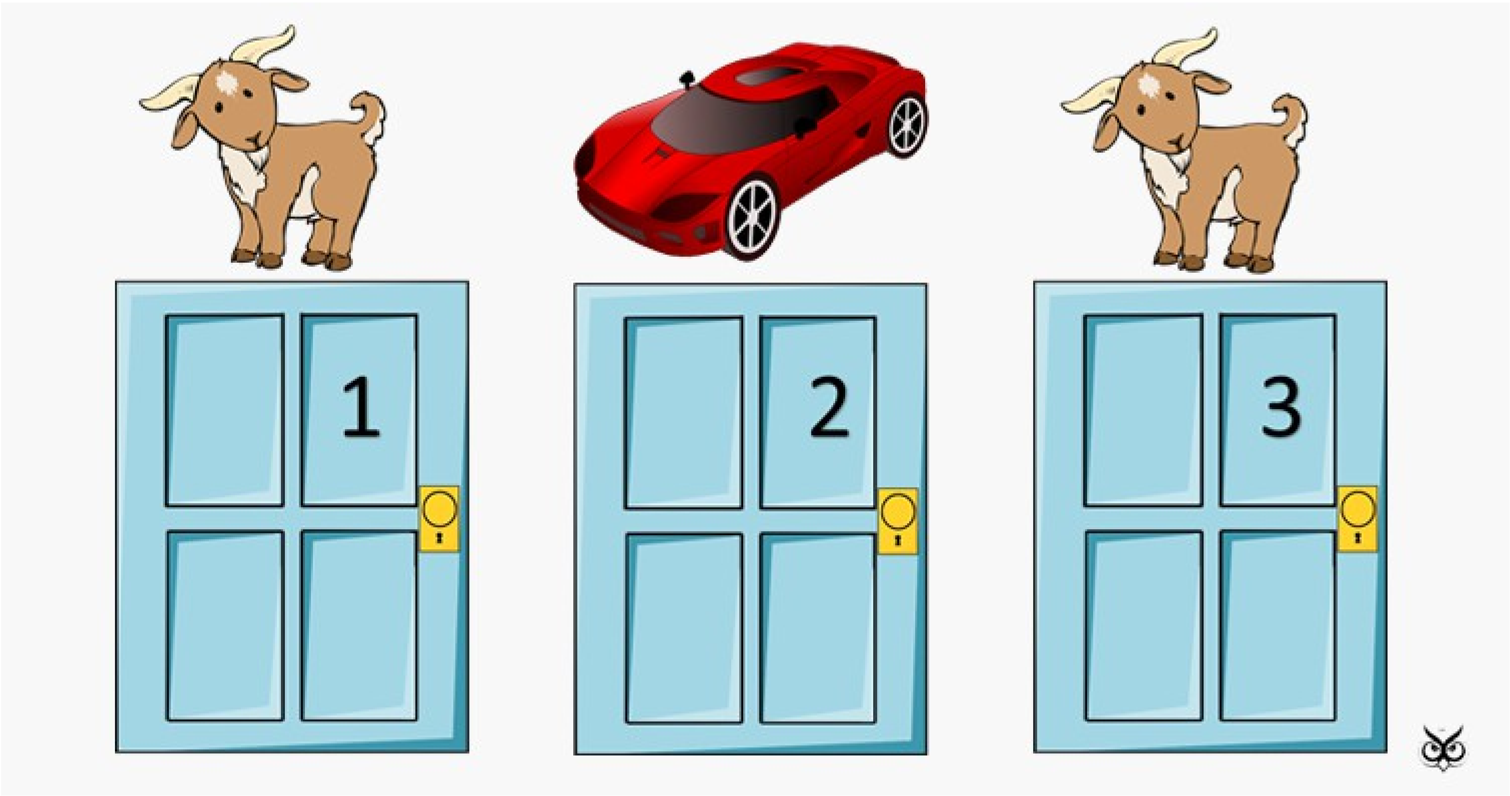


Image 2

Monty Hall Paradox

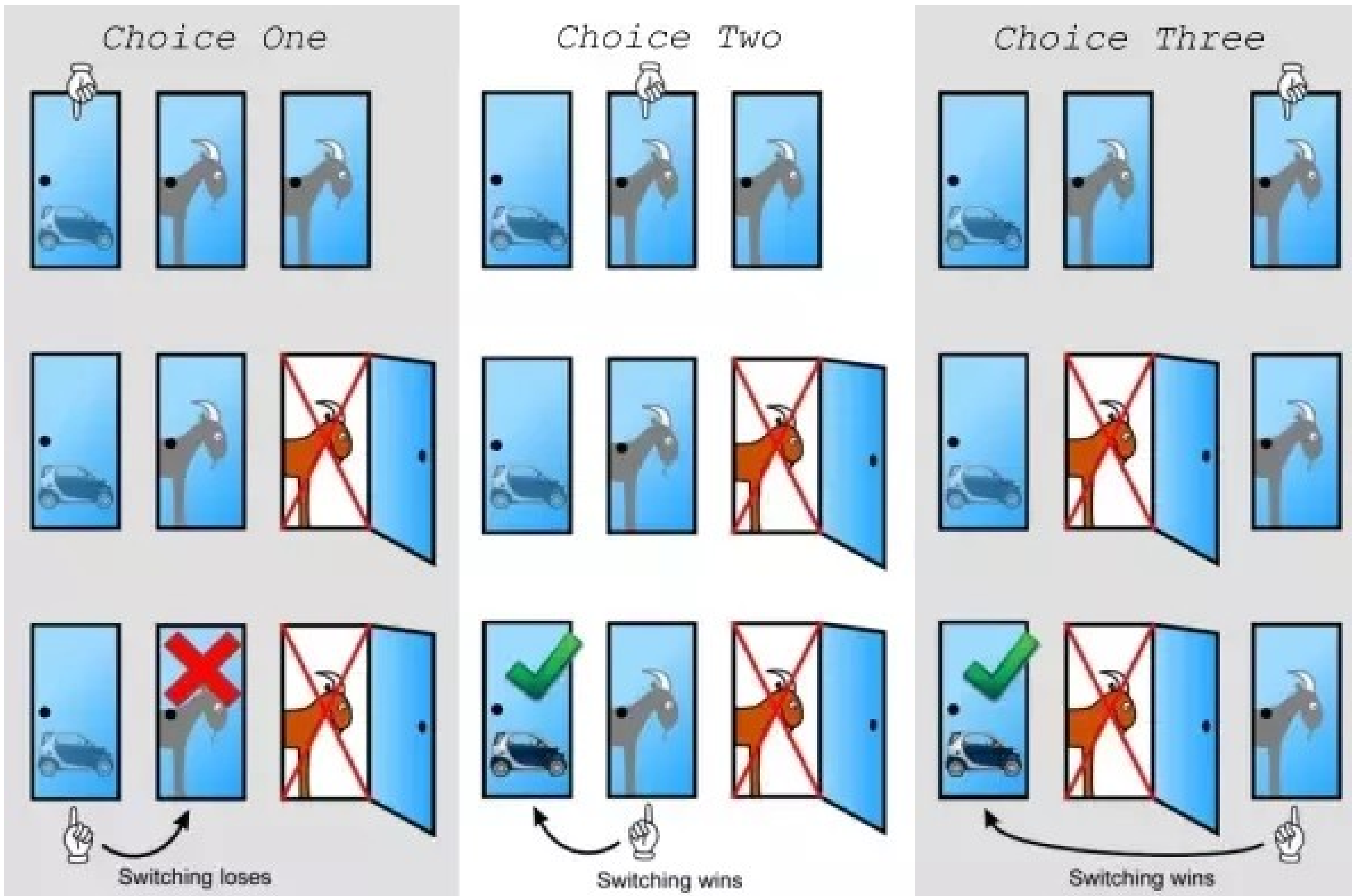
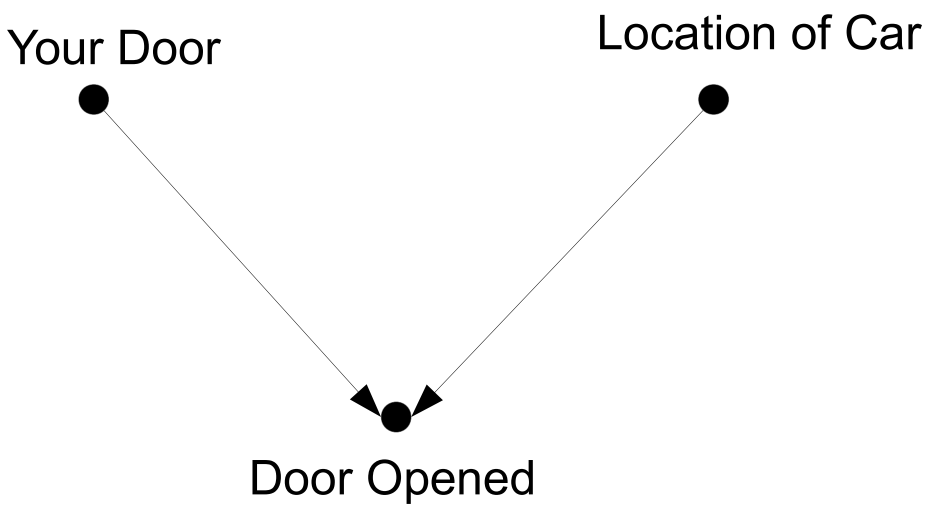


Image 3

Monty Hall Paradox



Monty Hall Paradox

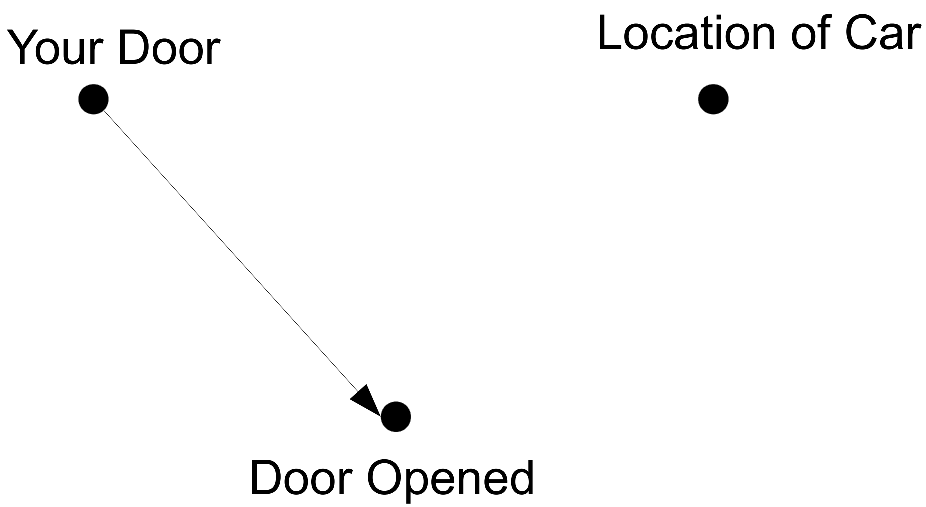
- Variation of the problem where door opened is random

Monty Hall Paradox

Chosen Door	Door with Car	Opened Door	Outome if you Switch	Outcome if you Stay
1	1	2	Lose	Win
1	1	3	Lose	Win
1	2	2	Lose	Lose
1	2	3	Win	Lose
1	3	2	Win	Lose
1	3	3	Lose	Lose

→ Opened door does not convey information. Switching and Staying are equally valid strategies.

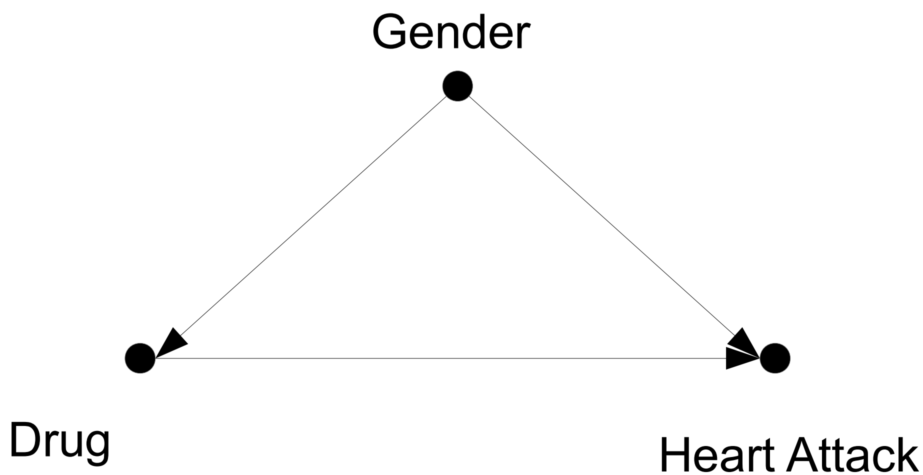
Monty Hall Paradox



Simpson's Paradox

	Control Group (No Drug)		Treatment Group (Took Drug)	
	Heart Attack	No Heart Attack	Heart Attack	No Heart Attack
Female	1	19	3	37
Male	12	28	8	12
Total	13	47	11	49

Simpson's Paradox



→ Confounder Bias!

Simpson's Paradox

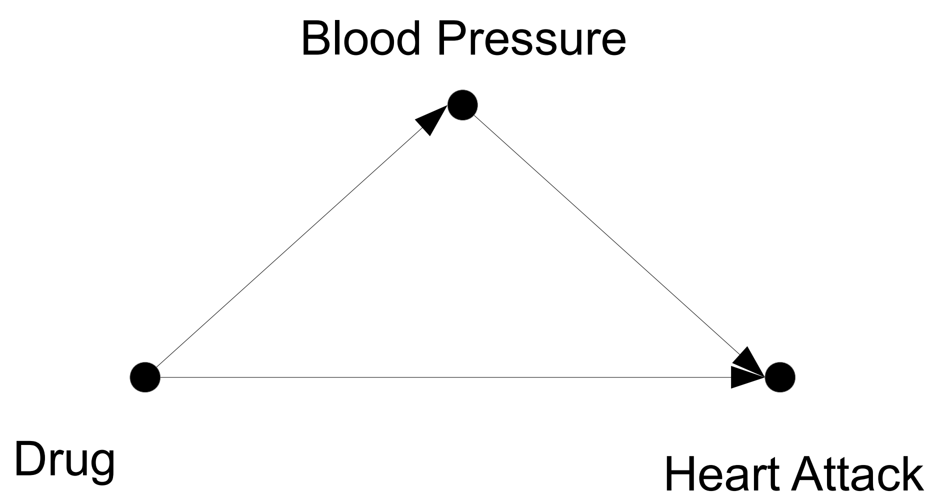
	Control Group (No Drug)	Treatment Group (Took Drug)
	Heart Attack Rate in Percent	Heart Attack Rate in Percent
Female	5	7.5
Male	30	40
Total	17.5	23.75

The drug seems to increase the risk of a heart attack

Simpson's Paradox

	Control Group (No Drug)		Treatment Group (Took Drug)	
	Heart Attack	No Heart Attack	Heart Attack	No Heart Attack
Low Blood Pressure	1	19	3	37
High Blood Pressure	12	28	8	12
Total	13	47	11	49

Simpson's Paradox



→ Even though the data is the same, the results differ depending on the model

Ascending To The 2nd Rung

Tools that can be used to predict the effects of intervention:

- Back-Door Adjustment
- Front-Door Adjustment
- Instrumental Variables
- Do-Calculus

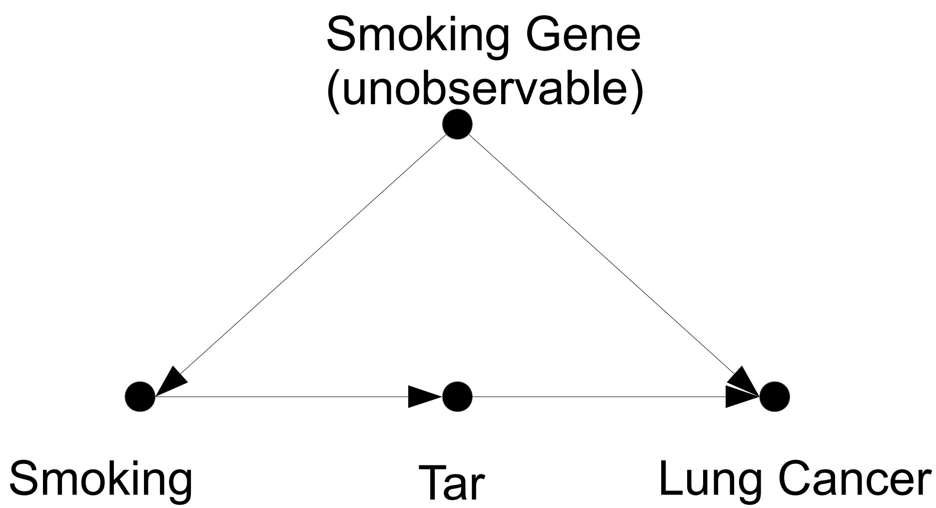
Back-Door Adjustment

- Adjust for all confounders
- Split data in groups where units have same values for confounders
- Estimate the effect for each group and then calculate the weighted average of all groups

Front-Door Adjustment

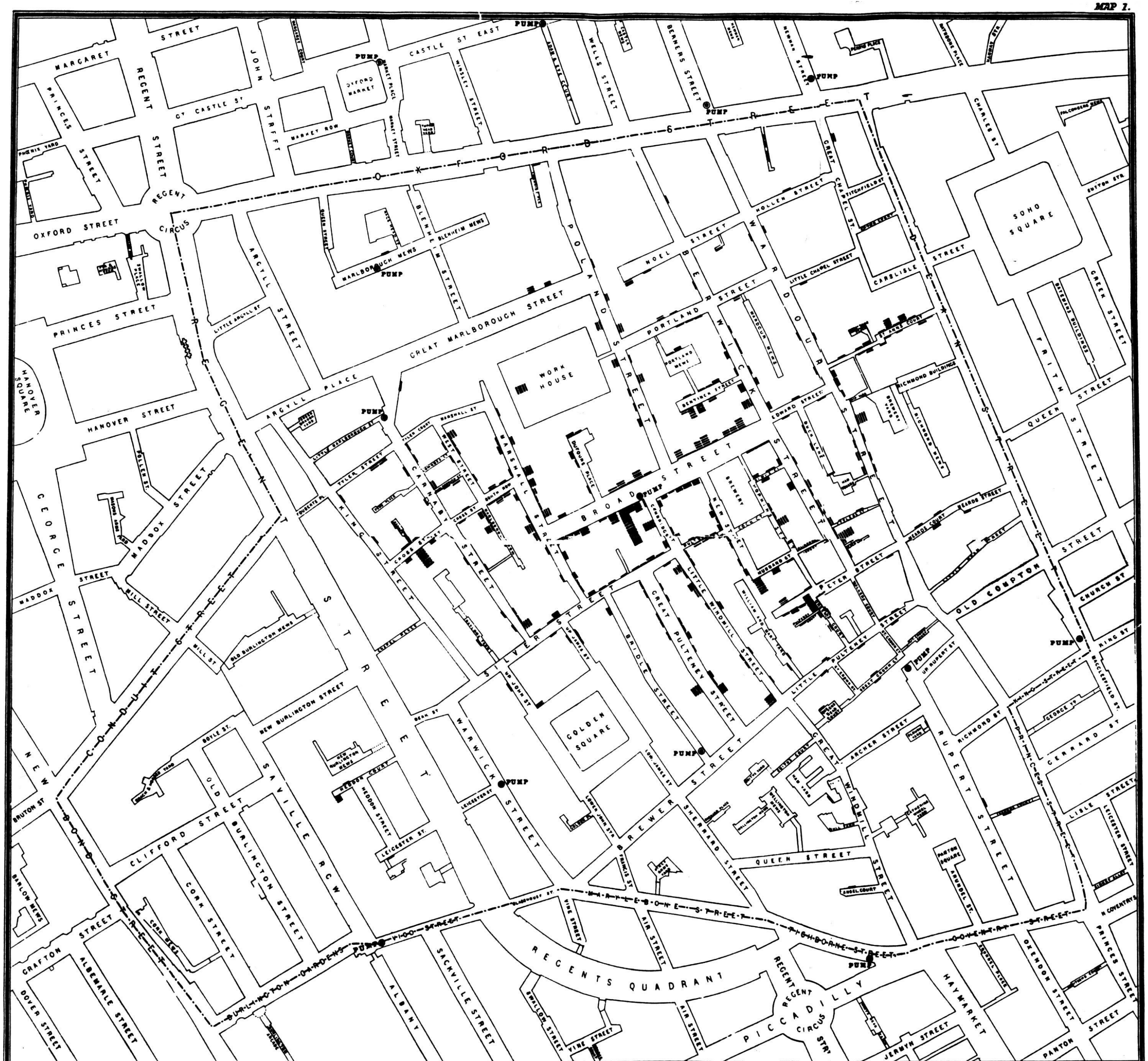
- Allows elimination of unobservable confounders
- Requires a mediator

Front-Door Adjustment



Adjust for Smoking and Tar.
Probability of Smoking to cause Lung Cancer =
P(tar | smoking) * P(lung cancer | tar)

MAP 1.

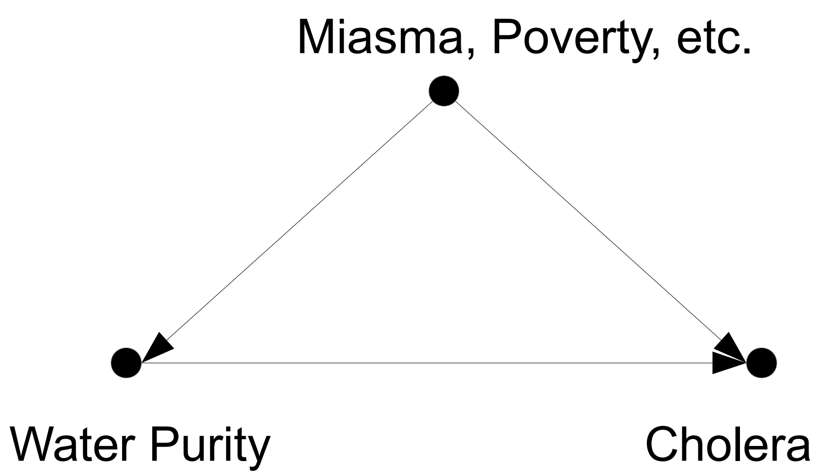


C. F. Cheffins, Lith. Southampton Bldgs. London.

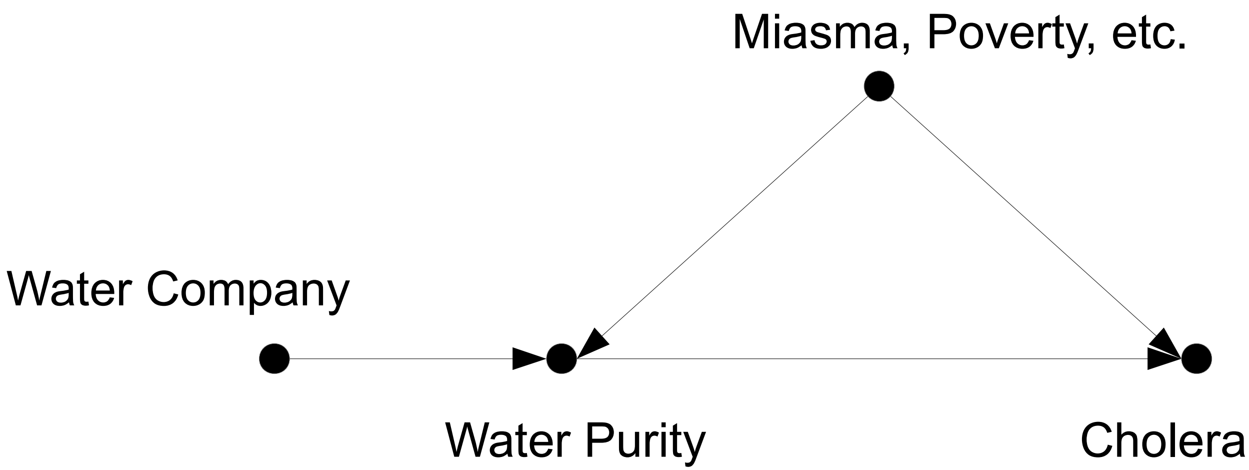
SCALE 30 INCHES TO A MILE.

Image 4

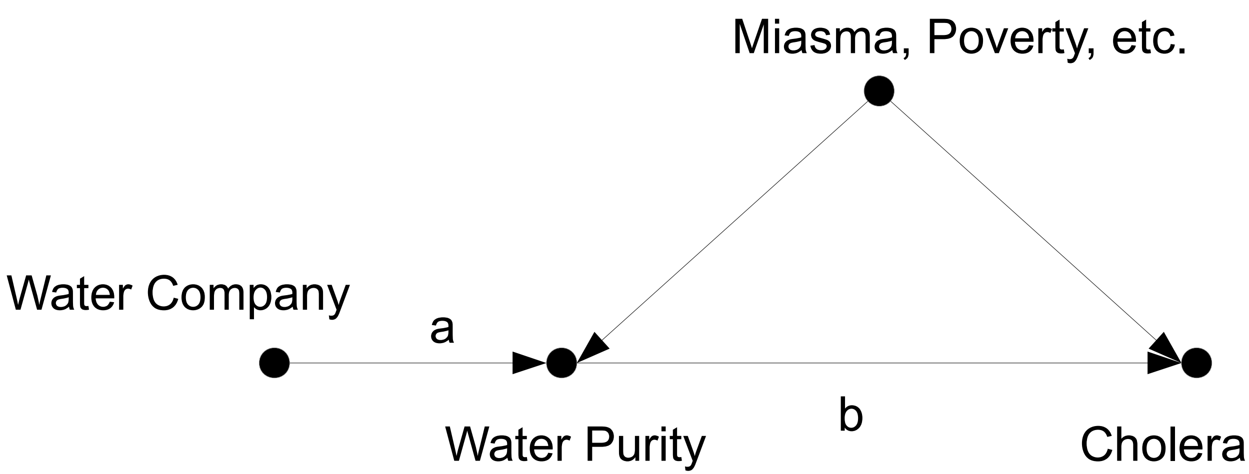
Instrumental Variables



Instrumental Variables



Instrumental Variables



Correlation between Water Company and Cholera = ab
Correlation between Water Company and Water Purity = a
Causal Effect of Water Purity on Cholera = ab/a = b

Do-Calculus

Allows to reshape expressions that use the do-operator into ones that can be calculated with only observational data

Do-Calculus

3 Rules:

1. Allows deletion of a variable W that has no effect on the outcome:

$$P(Y \mid do(X), Z, W) = P(Y \mid do(X), Z)$$

Do-Calculus

2. Allows transformation of do(X) to see(X), if a variable Z, that is controlled for, blocks all backdoor paths:

$$P(Y \mid do(X), Z) = P(Y \mid X, Z)$$

Do-Calculus

3. Allows removal of do(x), if there are no causal paths from X to Y:

$P(Y \mid do(X)) = P(Y)$

Counterfactuals

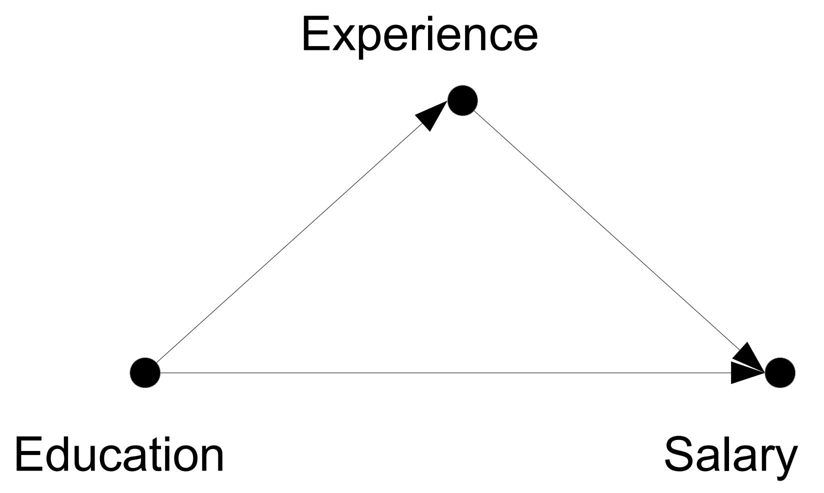
- Calculate difference in outcome Y if value of an effect X would have been different
- Probability of Necessity and Sufficiency

Counterfactuals

Employee	Experience	Education	Salary0	Salary1	Salary2
Alice	6	0	$81,000	?	?
Bert	9	1	?	$92,500	?
Caroline	9	2	?	?	$97,000
David	8	1	?	$91,000	?
Ernest	12	1	?	$100,000	?
Frances	13	0	$97,000	?	?

Education Levels:
0 = High School
1 = College
2 = Graduate

Counterfactuals



Counterfactuals

$S = \$65{,}000 + \$2{,}500 * \text{Experience} + \$5{,}000 * \text{Education} + U_s$

U_s is a variable that stands for any unobservable effects that affect salary but differ between individuals

$\text{Experience} = 10 – 4 * \text{ED} + U_{ex}$

Counterfactuals

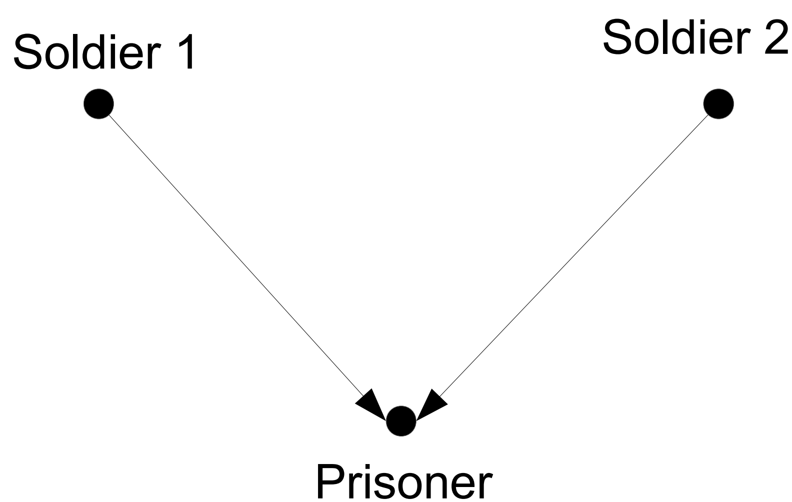
- Use data to calculate the unobservable factors from the data
- U_s(Alice) = $1,000
- U_{ex}(Alice) = -4
- Change the model: Education(Alice) = 1
- Calculate salary: $S_{ed=1}$ (Alice) = $65,000 + $2,500 * 2 + $5,000 * 1 + $1,000 = $76,000

→ Going to college is clearly not worth it!

Necessary and Sufficient Causes

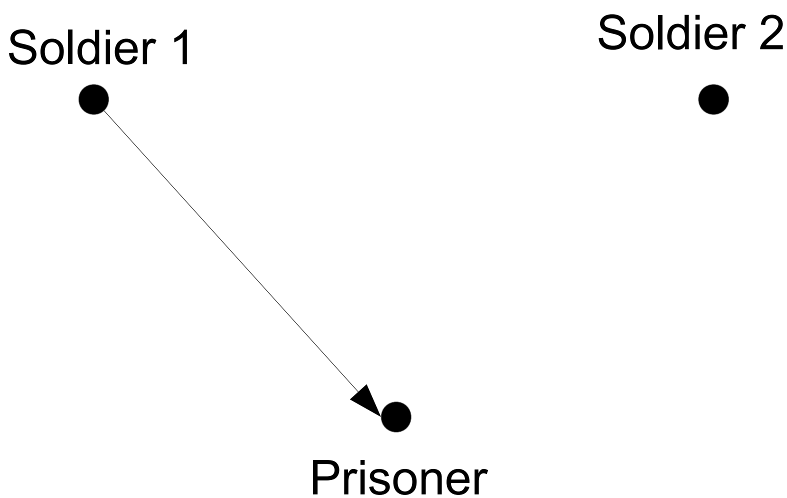
- Legal „but-for“ principle asks how necessary the actions of the accused were for the result
- PN: Probability of Necessity
- PS: Probability of Sufficiency

Necessary and Sufficient Causes



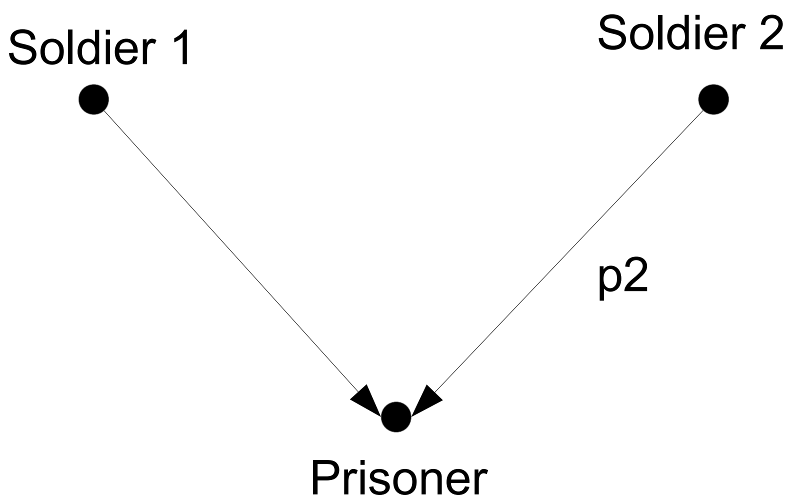
PN = 0
PS = 1

Necessary and Sufficient Causes



PN = 1
PS = 1

Necessary and Sufficient Causes

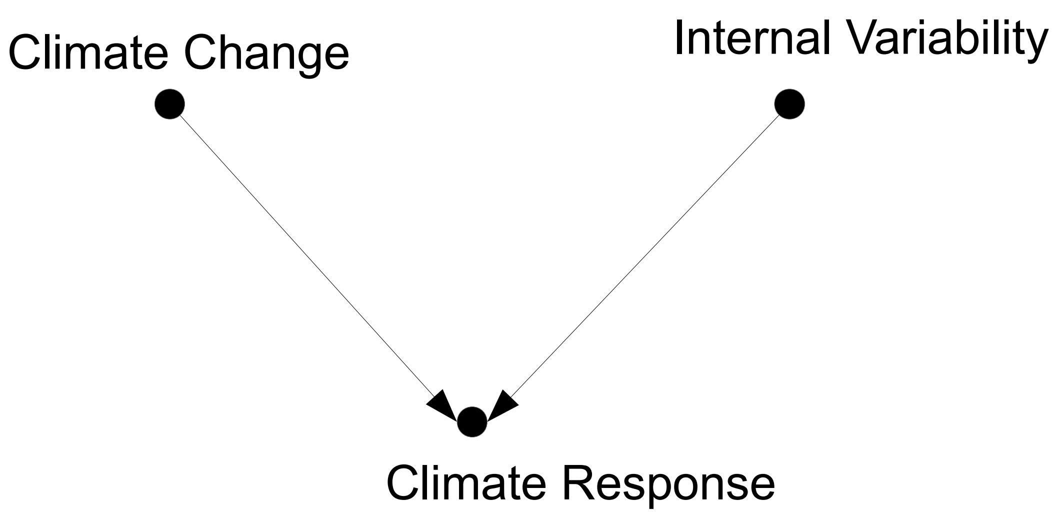


PN = 1 - p2
PS = 1

Necessary and Sufficient Causes

- Application of PN and PS in Climate Attribution Science
- Alexis Hannart: climate change has a PN of 0.9 and PS of 0.0072 for the 2003 European heat wave
- When looking at a longer time period, PS increases and PN decreases

Necessary and Sufficient Causes



Necessary and Sufficient Causes

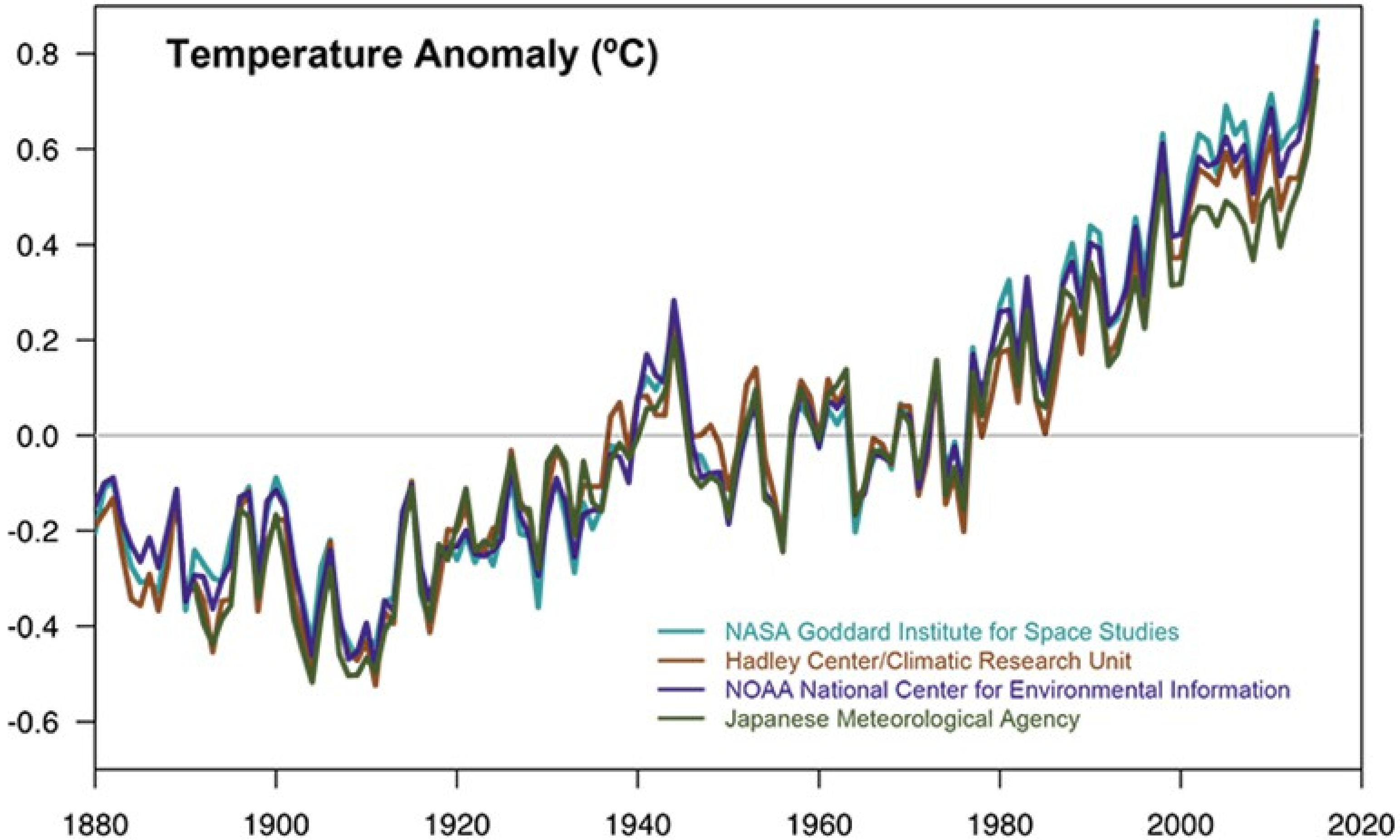
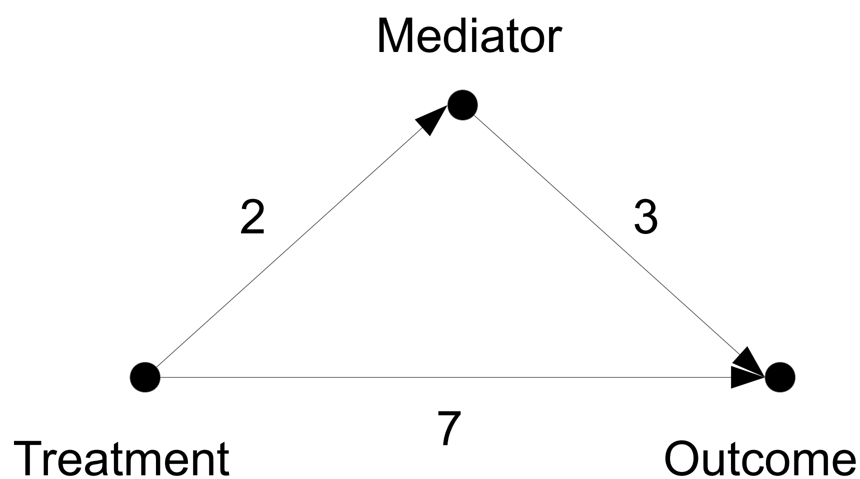


Image 6

Mediation: Defining of Direct and Indirect Effects

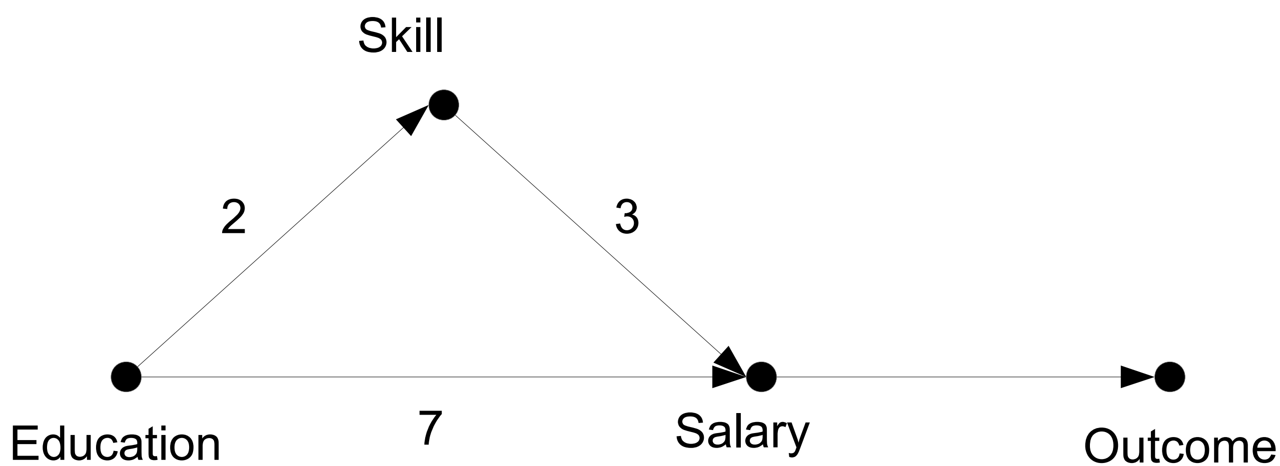
- Simple for linear models:
  Total Effect = Direct Effect + Indirect Effect

Mediation: Defining of Direct and Indirect Effects



Outcome = 7 + 2 * 3 = 13

Mediation: Defining of Direct and Indirect Effects



Applicant takes job if salary > 10
For Education = 1, Salary is 13 → Outcome = 1
However, isolated direct and indirect effects lead to Outcome = 0

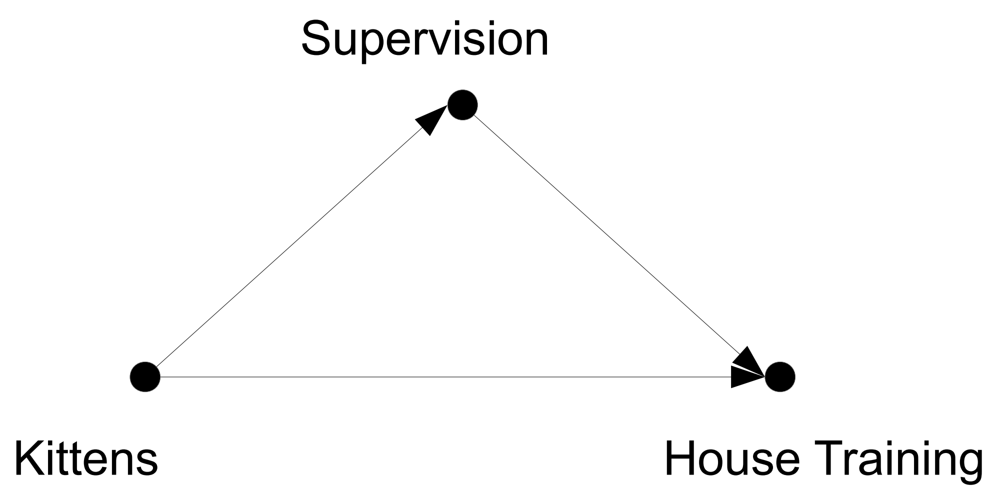
Mediation: Defining of Direct and Indirect Effects

- For nonlinear models, one must use counterfactuals
- Direct Effect: Change Cause X while holding Mediator M constant
  $DE = P(Y_{M=M_0} = 1 \mid do(X = 1)) -$
  $\qquad P(Y_{M=M_0} = 1 \mid do(X = 0))$

Mediation: Defining of Direct and Indirect Effects

- Indirect Effect: Change Mediator M while holding Cause X constant
  $IE = P(Y_{M=M_1} = 1 \mid do(X = 0)) -$
  $P(Y_{M=M_0} = 1 \mid do(X = 0))$

Mediation: Calculating of Direct and Indirect Effects



Causality and AI

- Deep learning programs are very succesful, but similar to a blackbox

  AlphaZero can't explain to humans, why it made a specific chess move
- Author's hope: AI that uses causal language can communicate with humans about the reasons of their actions

Sources

- Image 1: https://miro.medium.com/max/1088/1*c5BGrjbxszVGhALzwgPR4Q.png
- Image 2: https://www.norwegiancreations.com/wp-content/uploads/2018/10/montyhallproblem.png
- Image 3: https://qph.fs.quoracdn.net/main-qimg-7bc6bc567a79d8976796805553659f20.webp
- Image 4: https://upload.wikimedia.org/wikipedia/commons/2/27/Snow-cholera-map-1.jpg
- Image 5: https://d1w7fb2mkkr3kw.cloudfront.net/assets/images/book/lrg/9780/1419/9780141982410.jpg
- Image 6: https://climate.nasa.gov/system/internal_resources/details/original/1192_1309_consensus-graphic-2015-768px.jpg
- Pearl, Judea and Mackenzie, Dana. *The Book of Why* Penguin Books, 2019