Seeing Doing and Imagining

Dr. Judea Pearl’s view on Causal Inference in Statistics

Biography

-Computer Scientist

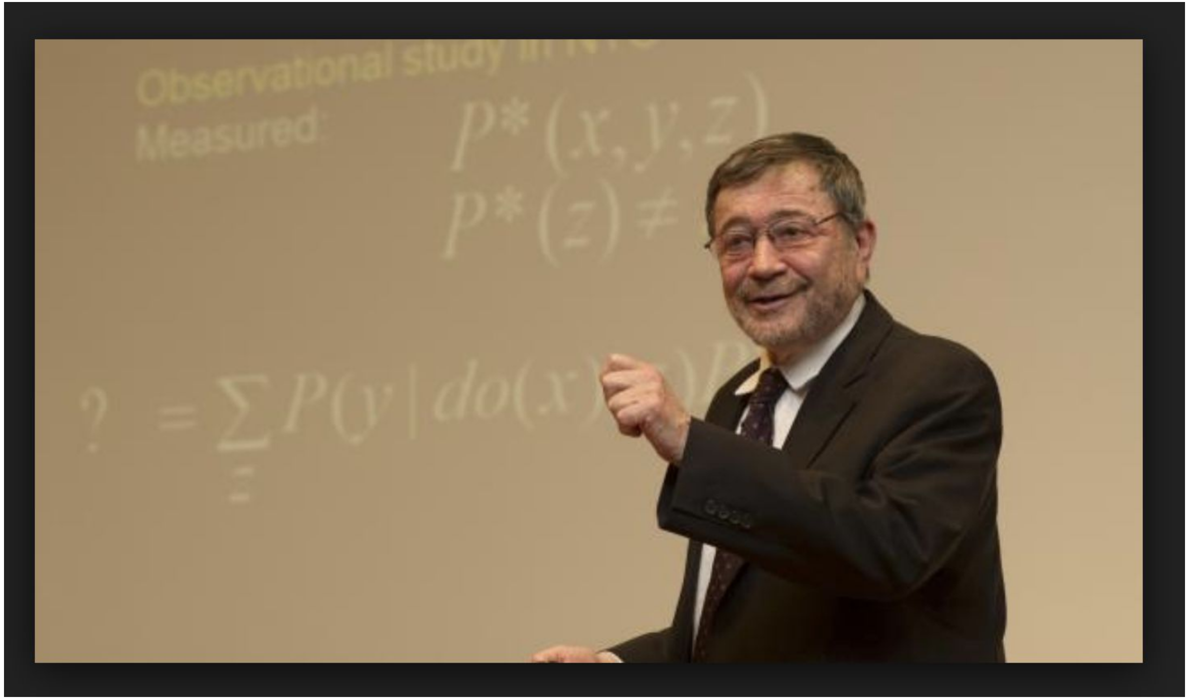
-Philosopher

-One of the developers of

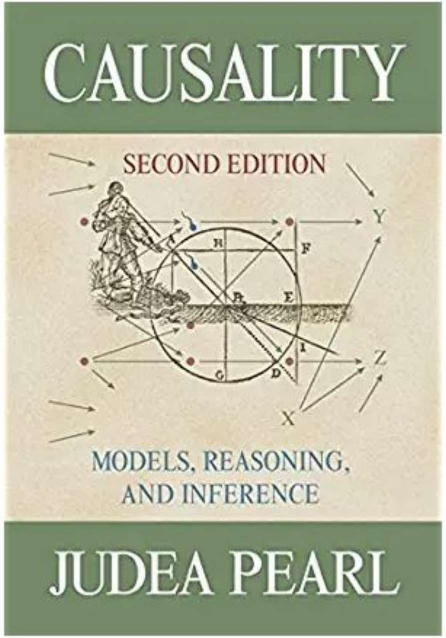
Bayesian Networks

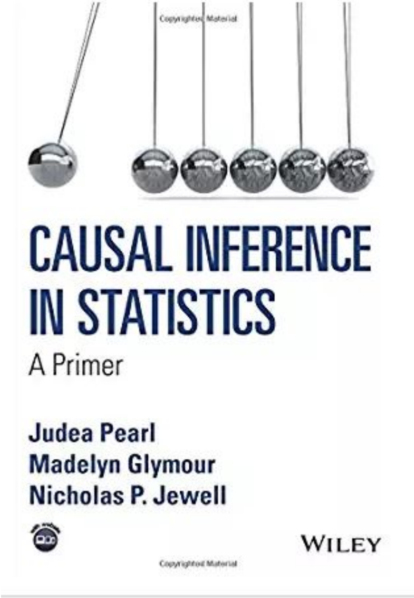
-2011 Winner of ACM Turing

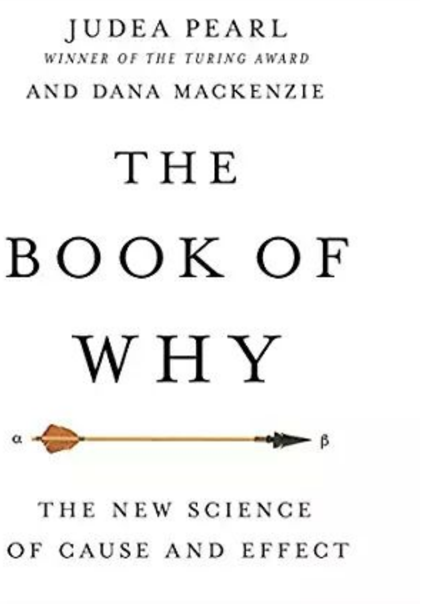
Award

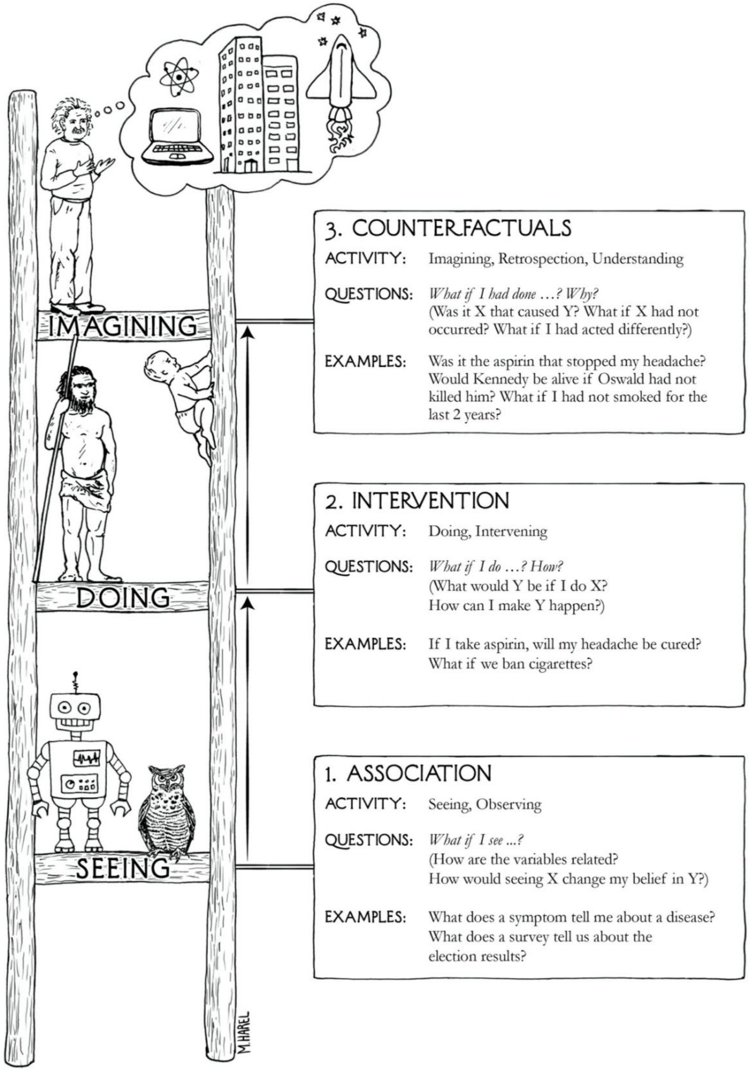


Books About Causality (By Pearl)









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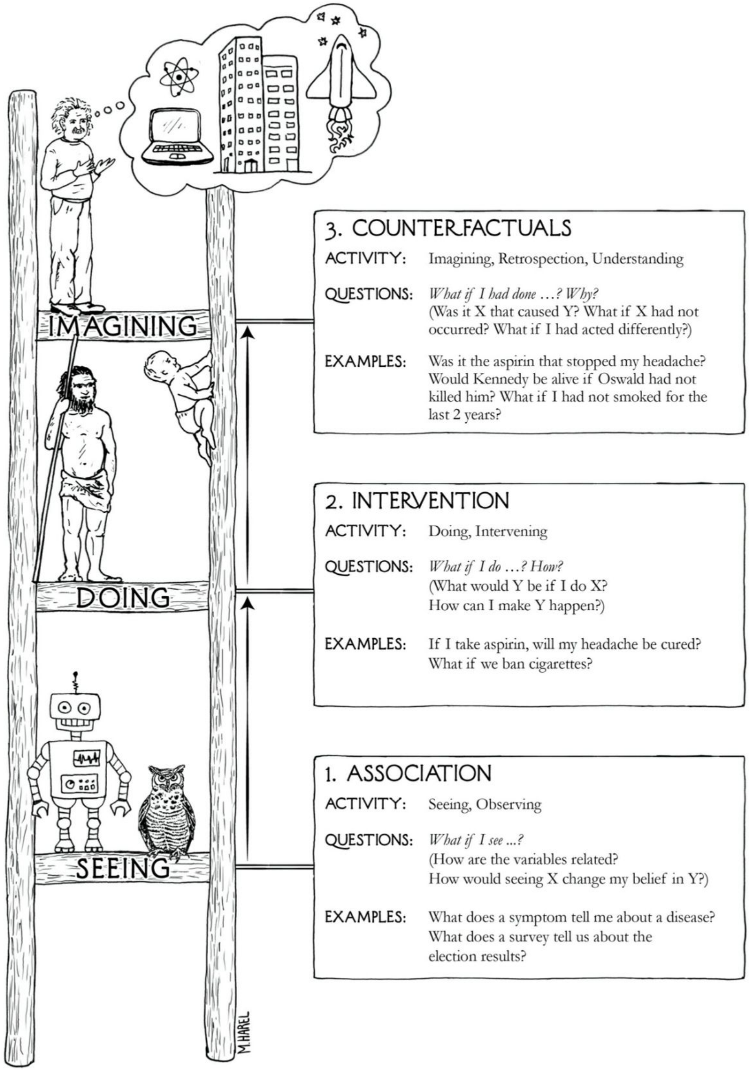
M. HAREL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Seeing

Seeing

History and Milestones:

--David Hume

--Frederick Galton

--Karl Pearson

Models:

--Graphical Models

--Confounder

--Collider

David Hume

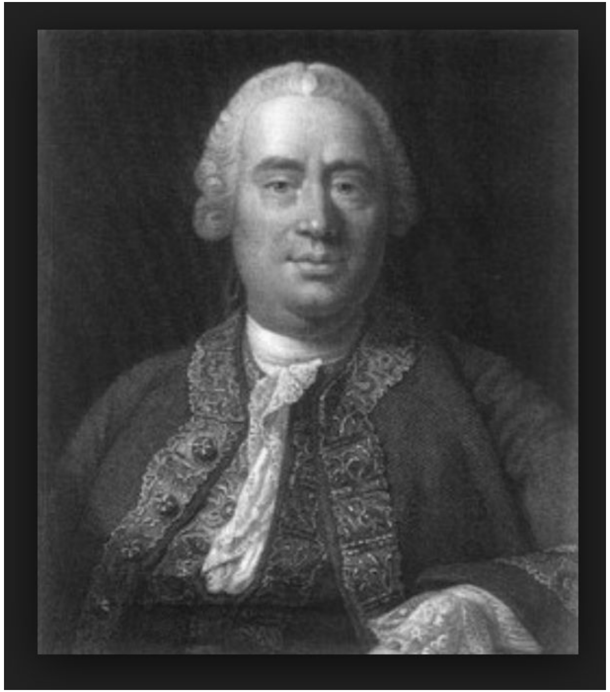
--18 Century philosopher

--Causality cannot be justified rationally

--Causality is result of metal or custom habit

--Attributable only to the experience of

“Constant Conjunction”



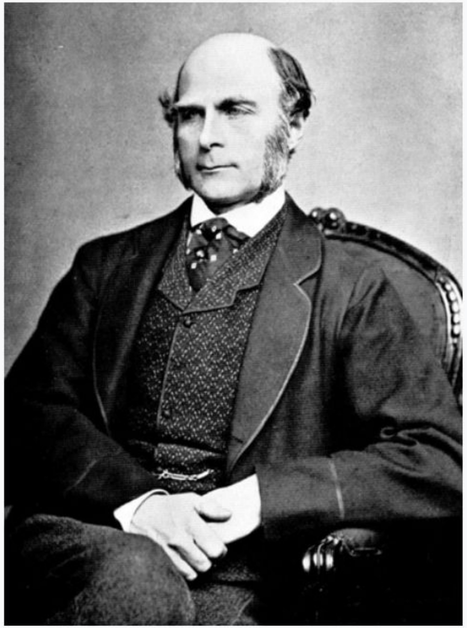
Galton

--19 Century statistician

--Toward causality but found correlation

--Popularized the word regression

Sir Francis Galton



Pearson

--Galton’s student

--Define causation as a special case of correlation

1. when correlation coefficient is 1 and

2. x and y are deterministic(which can never be proven)

--Completely ignored intervention and conterfacture

Karl Pearson
FRS

Notation

V: Endogenous variables {X,Y,Z}

U: Exogenous variables {Ux, Uy, Uz}

F: Functions {Fx, Fy, Fz}

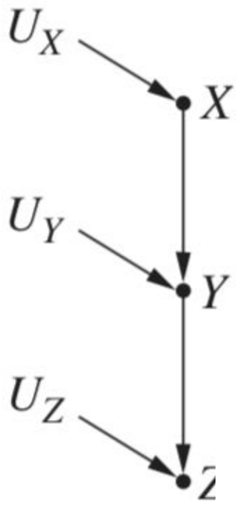
Every endogenous variable in a model is a descendant of at least one exogenous variable.

Exogenous variables cannot be descendants of any other variables, and in particular, cannot be a descendant of an endogenous variable; they have no ancestors and are represented as *root* nodes in graphs.

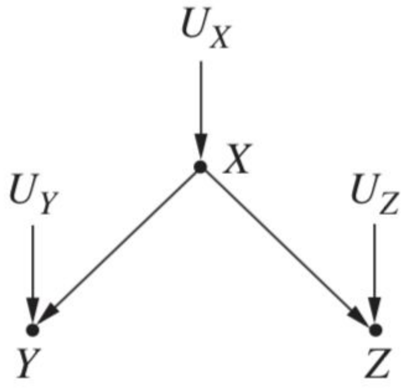
If we know the value of every exogenous variable, then using the functions in *f* , we can determine with perfect certainty the value of every endogenous variable.

Chain and Forks

Rule 1 (Conditional Independence in Chains) *Two variables, X and Z are conditionally independent given Y, if there is only one unidirectional path between X and Y and Z is any set of variables that intercepts that path.*



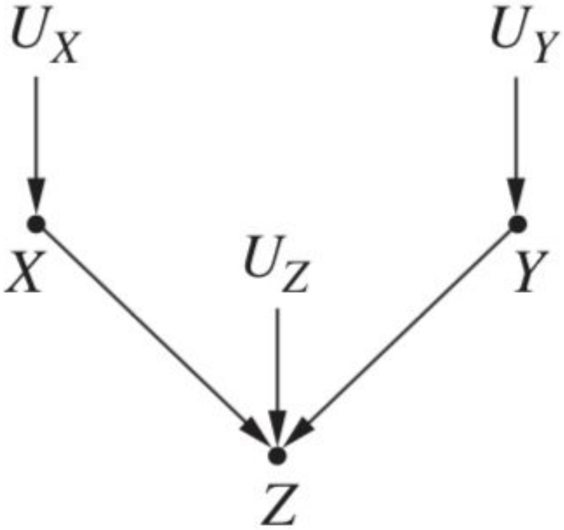
Rule 2 Conditional Independence in Forks) *If a variable X is a common cause of variables Y and Z, and there is only one path between Y and Z, then Y and Z are independent conditional on X.*



Collider

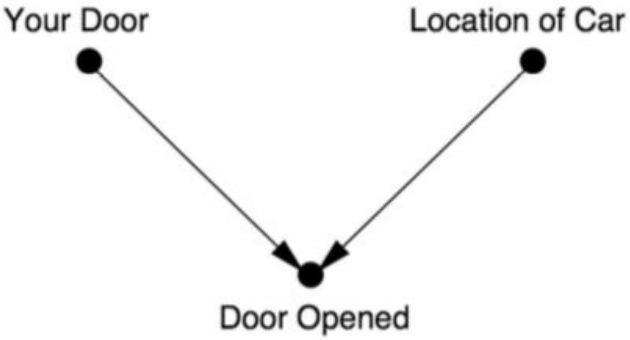
Rule 3 (Conditional Independence in Colliders) *If a variable Z is the collision node between two variables X and Y, and there is only one path between X and Y, then X and Y are unconditionally independent but are dependent conditional on Z and any descendants of Z.*

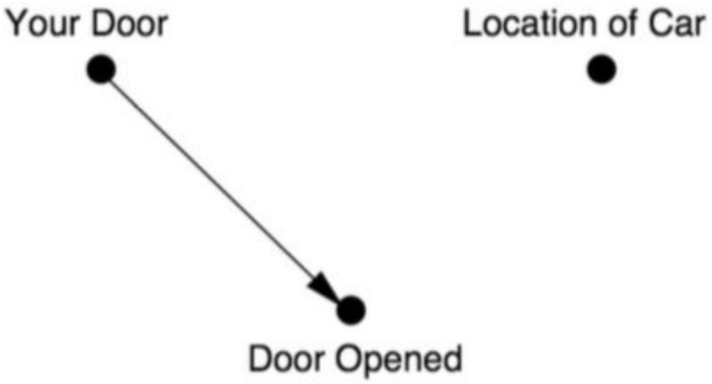
(The grass rain, sprinkler example)



Examples of Collider

Monty Hall Problem



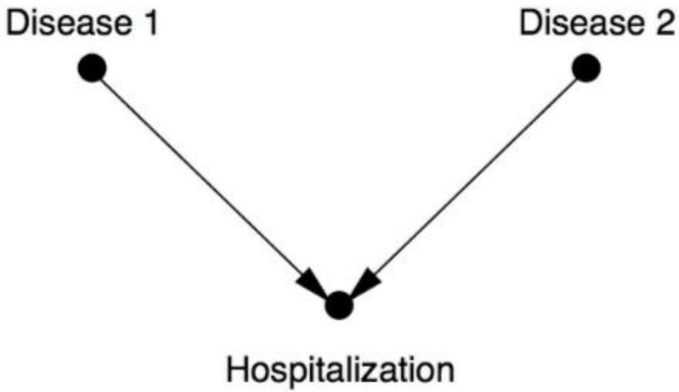


Collider Bias

Berkson's Paradox

Two traits are independent from each other(or negative related) will appear to be positive related once conditioned on a collider (or a descendent of a collider)

Sometimes as selection bias

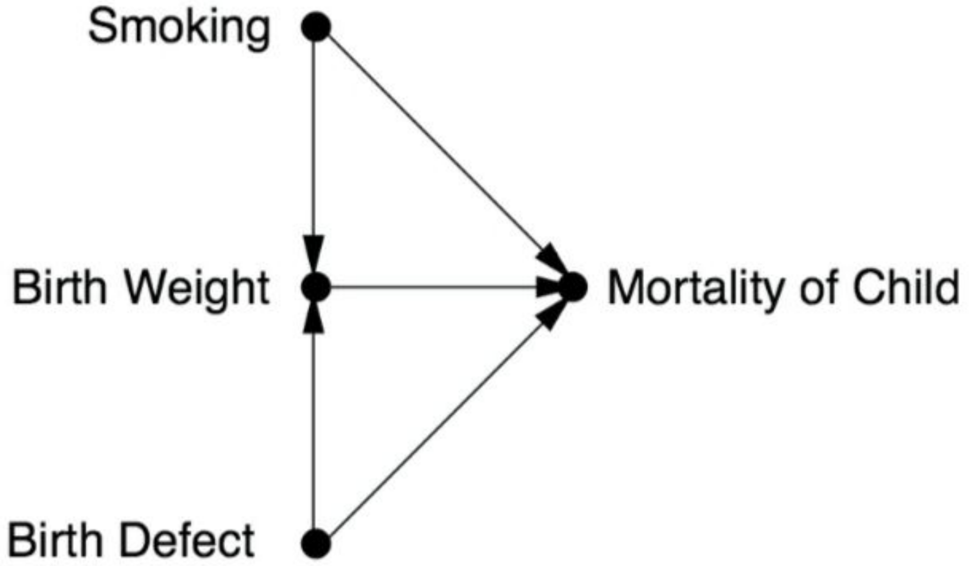


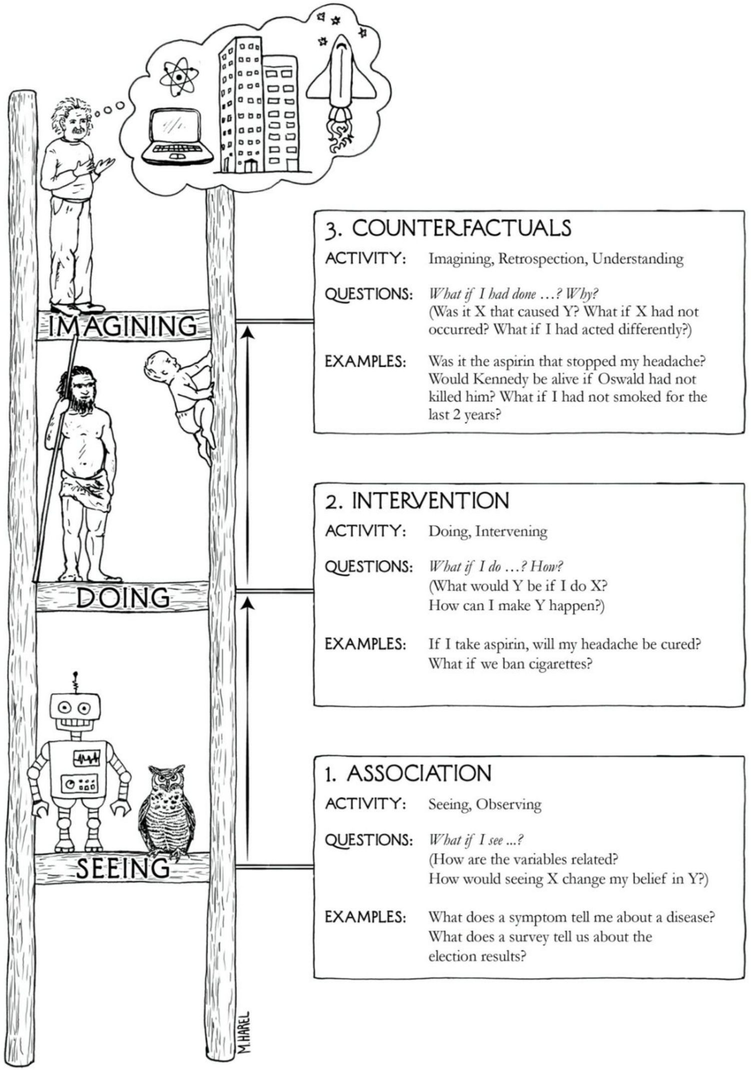
Newborn Smoking Study

Mid 1960, researcher pointed out that mother’s smoking during pregnancy seemed to benefit the health or her newborn baby.

Reason:

Newborn baby from smoking mother h a better survival rate than non-smokin mother.

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Doing

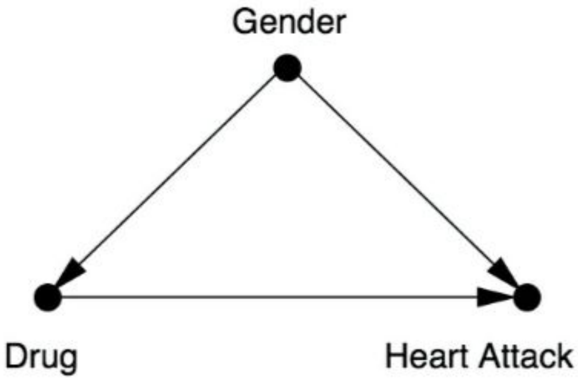
R. A. Fisher

--Statistician

--Geneticist

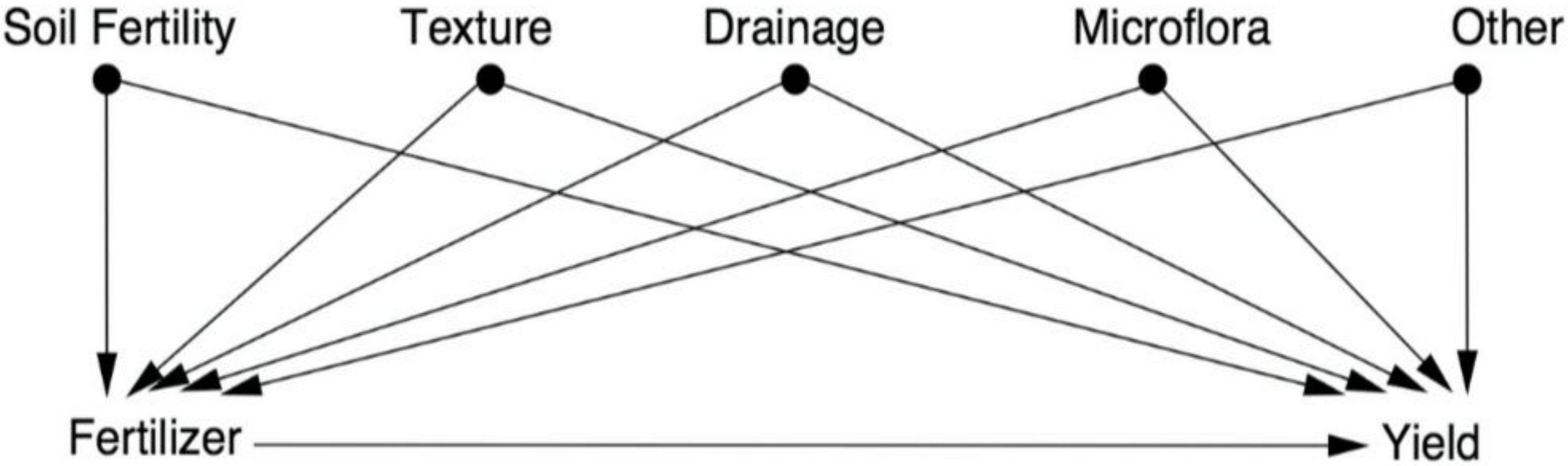
--Expert in experiment design

Confounder

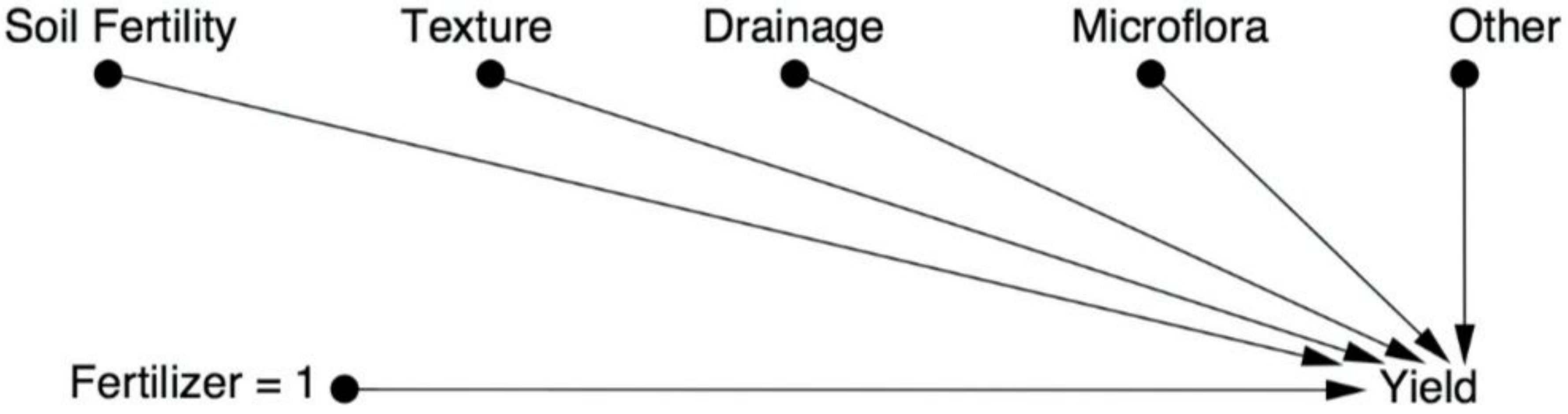


	Control Group (No Drug)		Treatment Group (Took Drug)	
	Heart attack	*No heart attack*	*Heart attack*	*No heart attack*
Female	1	19	3	37
Male	12	28	8	12
Total	13	47	11	49

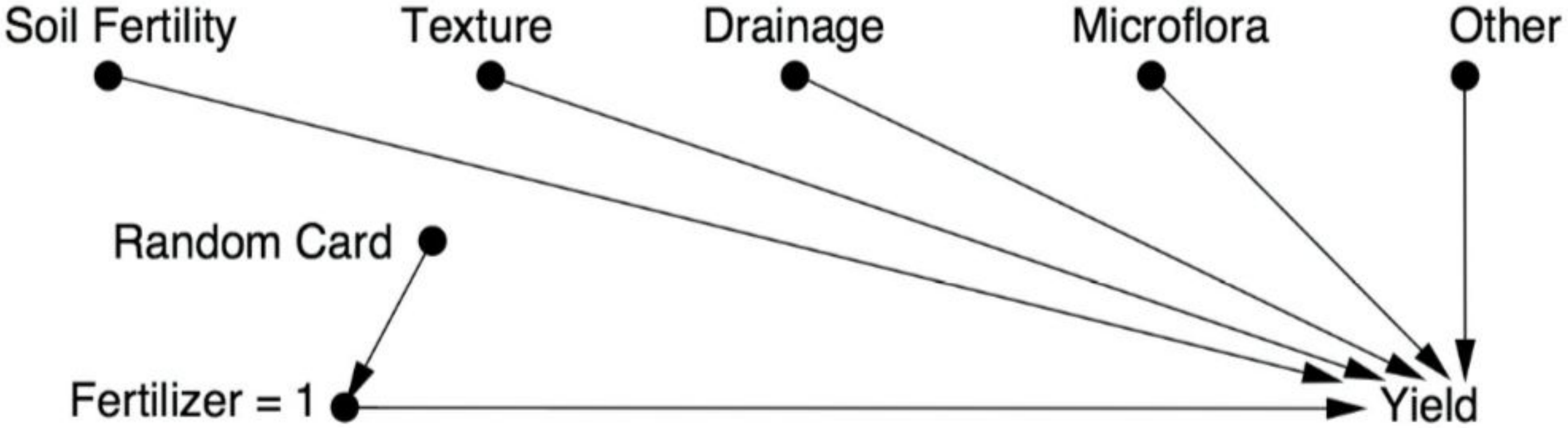
Many Confounders



Adjust for confounders



RCT by Fisher



Intervention

--Randomized Controlled Trials, the golden standard of intervention

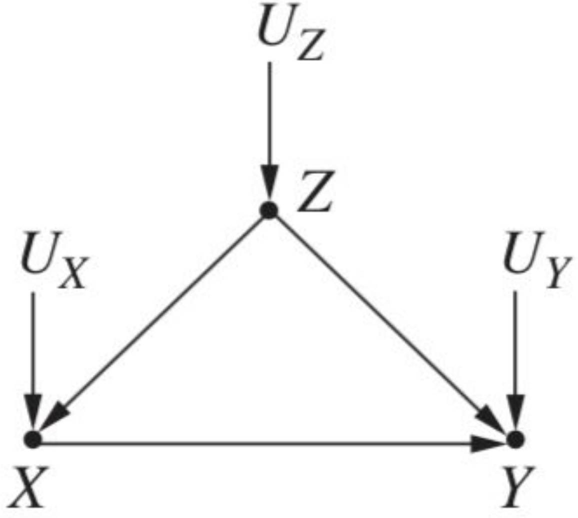
1. Solved potential confounding bias
2. Quantified uncertainty

--But always check if the design actually solved the problem

(Story of working condition and production in a factory)

New Notation

$$P(Y = 1|do(X = 1)) - P(Y = 1|do(X = 0))$$



Adjustment

Rule 1 (The Causal Effect Rule) *Given a graph G in which a set of variables PA are designated as the parents of X, the causal effect of X on Y is given by*

$$P(Y = y|do(X = x)) = \sum_z P(Y = y|X = x, PA = z)P(PA = z) \tag{3.6}$$

Back Door

Definition 3.3.1 (The Backdoor Criterion) *Given an ordered pair of variables (X, Y) in a directed acyclic graph G, a set of variables Z satisfies the* backdoor criterion *relative to (X, Y) if no node in Z is a descendant of X, and Z blocks every path between X and Y that contains an arrow into X.*

If a set of variables Z satisfies the backdoor criterion for X and Y, then the causal effect of X on Y is given by the formula

$$P(Y = y|do(X = x)) = \sum_z P(Y = y|X = x, Z = z)P(Z = z)$$

1. We block all spurious paths between *X* and *Y*.

2. We leave all directed paths from *X* to *Y* untouched.

3. We create no newpaths.

Example

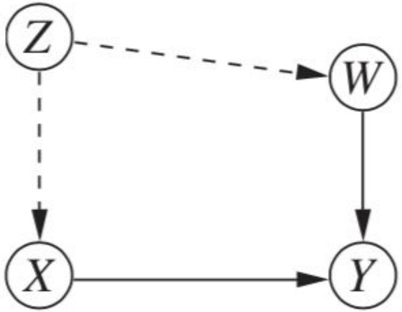


Figure 3.6 A graphical model representing the relationship between a new drug (X), recovery (Y), weight (W), and an unmeasured variable Z (socioeconomic status)

$$P(Y = y|do(X = x)) = \sum_{w} P(Y = y|X = x, W = w)P(W = w)$$

$$P(y|do(x)) = P(y|x)$$

Front Door

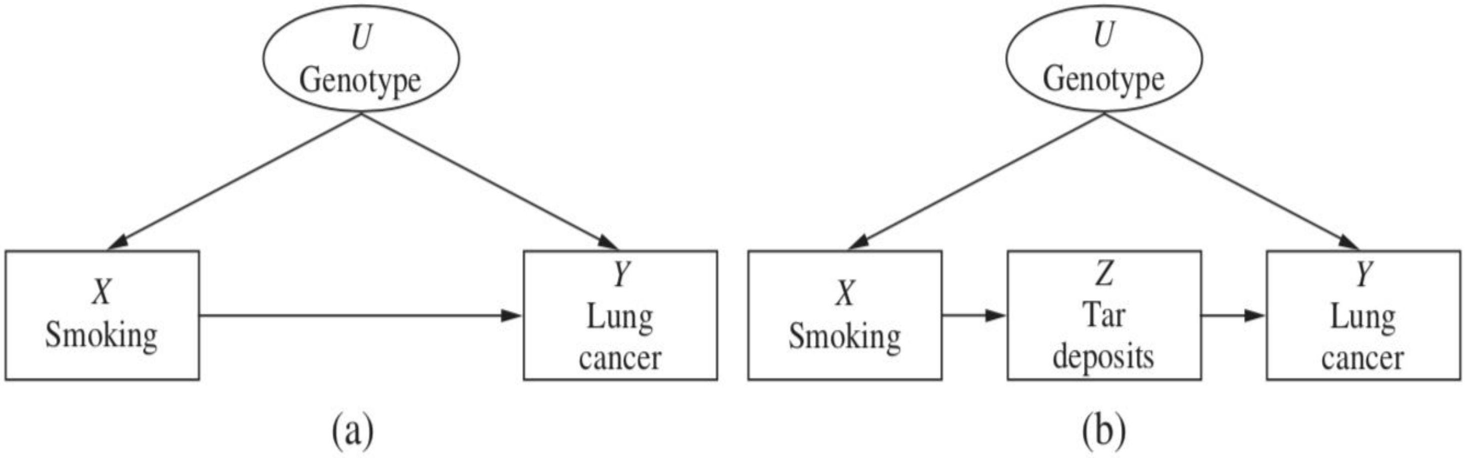


Figure 3.10 A graphical model representing the relationships between smoking (X) and lung cancer (Y), with unobserved confounder (U) and a mediating variable Z

Front Door

Definition 3.4.1 (Front-Door) *A set of variables Z is said to satisfy the front-door criterion relative to an ordered pair of variables* (X, Y) *if*

1. *Z intercepts all directed paths from X to Y.*
2. *There is no unblocked path from X to Z.*
3. *All backdoor paths from Z to Y are blocked by X.*

Front Door

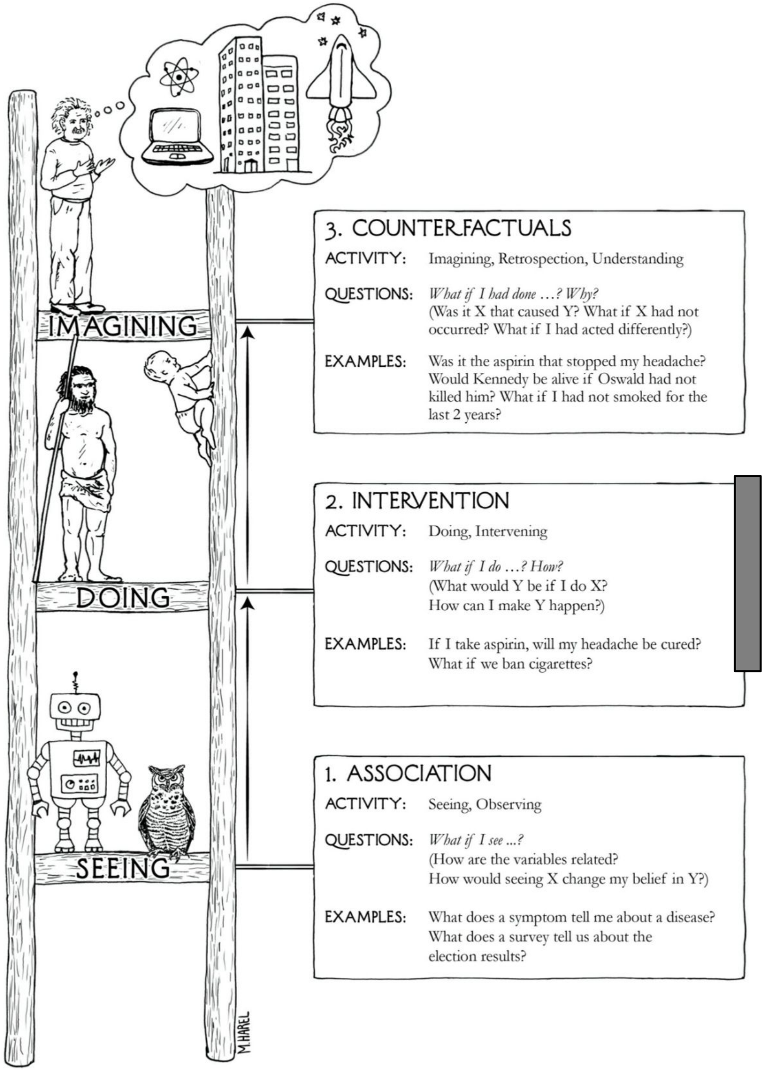
$$P(Z = z|do(X = x)) = P(Z = z|X = x)$$

$$P(Y = y|do(Z = z)) = \sum_x P(Y = y|Z = z, X = x)$$

$$P(Y = y|do(X = x)) = \sum_z P(Y = y|do(Z = z))P(Z = z|do(X = x))$$

$$P(Y = y|do(X = x)) =$$

$$\sum_z \sum_{x'} P(Y = y|Z = z, X = x')P(X = x')P(Z = z|X = x)$$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Imagining

Counterfactures

Notation:

“Do” operator

$$E(Y_{X=1} | X = 0, Y = Y_0 = 1)$$

$$E[Y | do(X = x)]$$

Three Steps

(i) Abduction: Use evidence $E = e$ to determine the value of U.

(ii) Action: Modify the model, M, by removing the structural equations for the variables in X and replacing them with the appropriate functions $X = x$, to obtain the modified model, Mx.

(iii) Prediction: Use the modified model, Mx, and the value of U to compute the value of Y, the consequence of the counterfactual.

Topic skipped

IP weighting

Mediation

TE, DE, NDE, NID

Causal Inference in Linear Systems(Partial regression)