An Ecological Alternative to Formal Approaches to External Validity

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UNIVERSITY OF JOHANNESBURG

Presentation Outline

1 External validity (EV) /Causal transportability

I briefly describe the problem of external validity. I explain the problem of transporting causal relationships, a type of EV inference.

2 The DAG/SEM Approach to Causal Identification

I sketch some background about the DAG/SEM approach to causality and show how it is meant to handle causal identification problems.

3 The DAG/SEM Approach to EV/transportability

I outline Pearl and Barenboim's treatment of causal transportability and distil it into advice to experimenters wanting to transport causal relationships.

4 An Ecological Alternative

I end by proposing some alternative advice about causal transportation / EV, inspired by an analogy with eco-systems.

My Goal Today

- Not a general critique of Pearlian DAG/SEM approach to causation
- Rather a focused assessment of the limitations of DAG/SEM approach specifically as applied to the EV/causal transportation problem
- I present my eco-systems alternative as pragmatic advice to experimenters who have to make inferences regarding transporting causal relationships

Caveats/Limitations

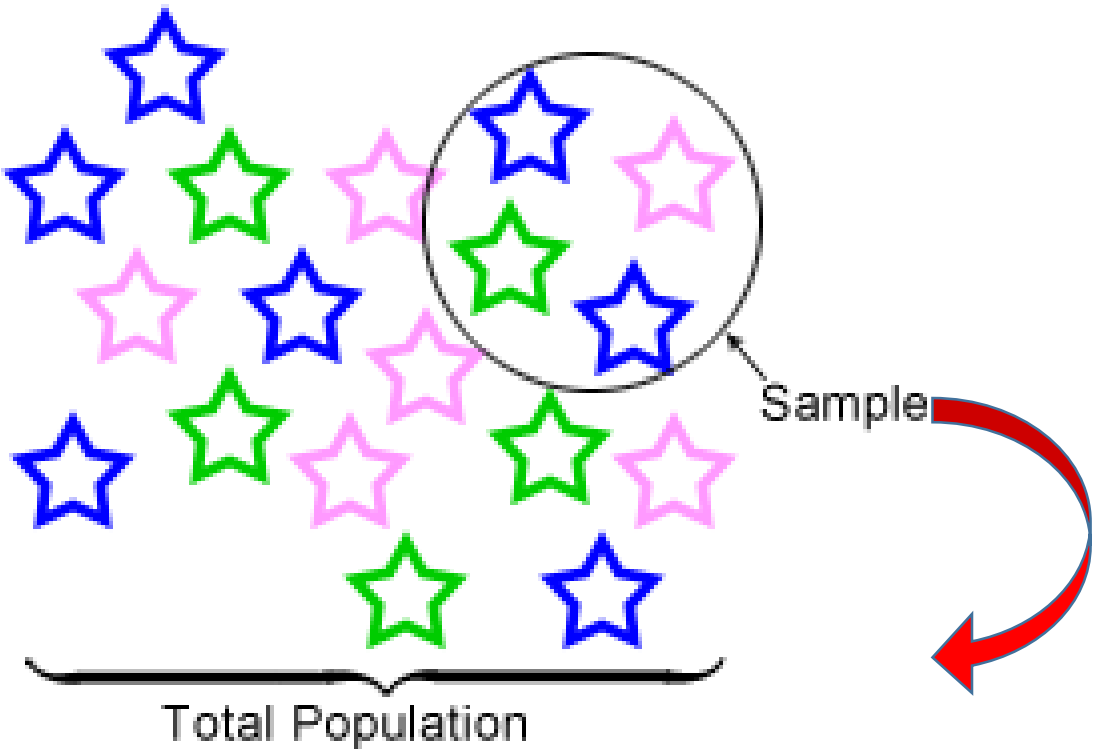
$$P^*(y \mid \mathrm{do}(x), z)$$

$$= \sum_{\text{age}} P^*(y \mid \mathrm{do}(x), z, \text{age}) P^*(\text{age} \mid \mathrm{do}(x), z)$$

$$= \sum_{\text{age}} P^*(y \mid \mathrm{do}(x), \text{age}) P^*(\text{age} \mid z)$$

$$= \sum_{\text{age}} P(y \mid \mathrm{do}(x), \text{age}) P^*(\text{age} \mid z).$$

External Validity (EV) / Causal Transportability



External Validity / Causal Transportability

- Pearl and Barenboim (2014) ‘External Validity: From do-calculus to Transportability Across Populations’: ‘P&B’ from here on -

- ‘The generalizability of empirical findings to new environments, settings or populations, often called “external validity,” is essential in most scientific explorations.’

- ‘This paper treats a particular problem of generalizability, called “transportability,” defined as a license to transfer causal effects learned in experimental studies to a new population, in which only observational studies can be conducted.’

Pearl and Barenboim (2014), Abstract

What’s a Pearlian (Causal) DAG/SEM?

- DAG = Directed Acyclical Graph
- SEM = Structural Equation Model

A Simple Example

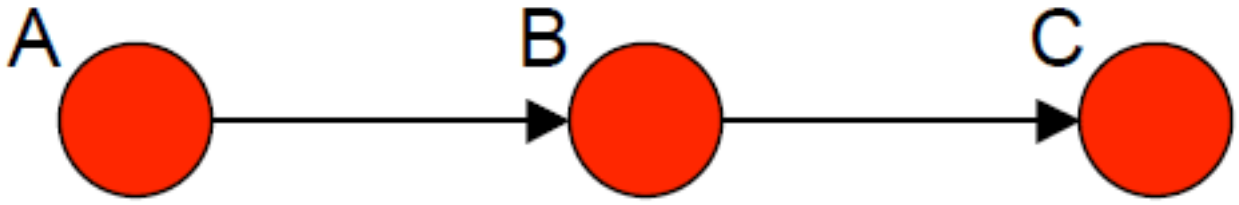


Figure 1

Hall (2007), p.4

DAG/SEM

Directed graph for figure 1

$$C \Leftarrow B$$

$$B \Leftarrow A$$

Hall (2007), pp. 6-7.

A Less Simple Case

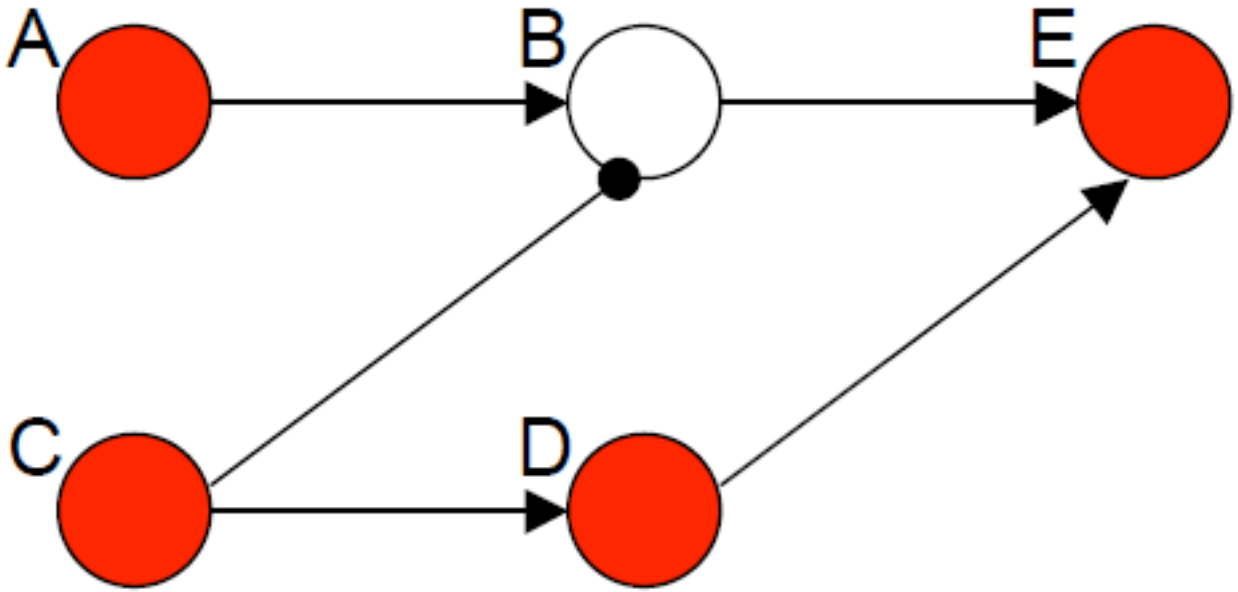
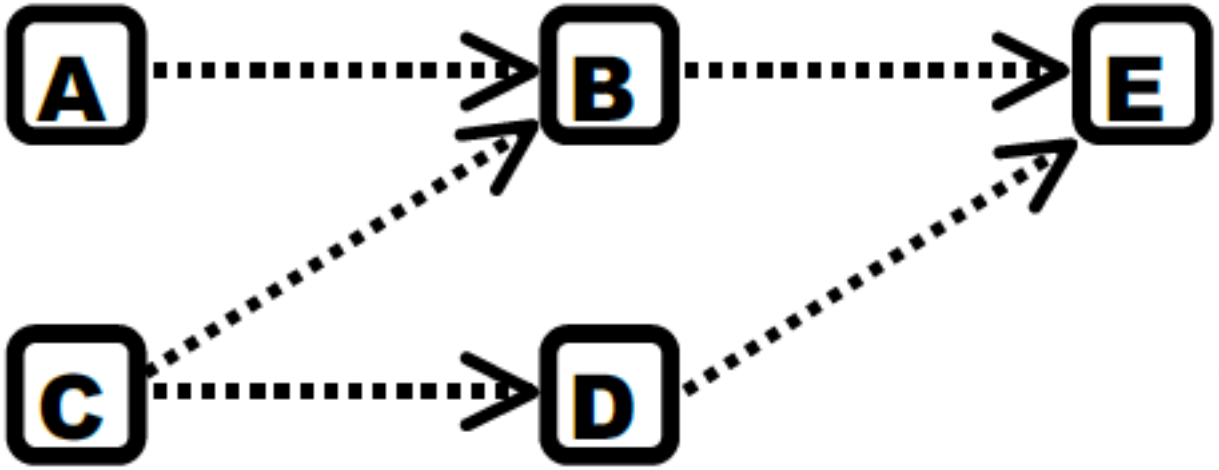


Figure 2

Hall (2007), p.4

DAG + SEM



Directed graph for figure 2

And here are the structural equations:

$$E \Leftarrow B + D - BD$$

$$D \Leftarrow C$$

$$B \Leftarrow A(1 - C)$$

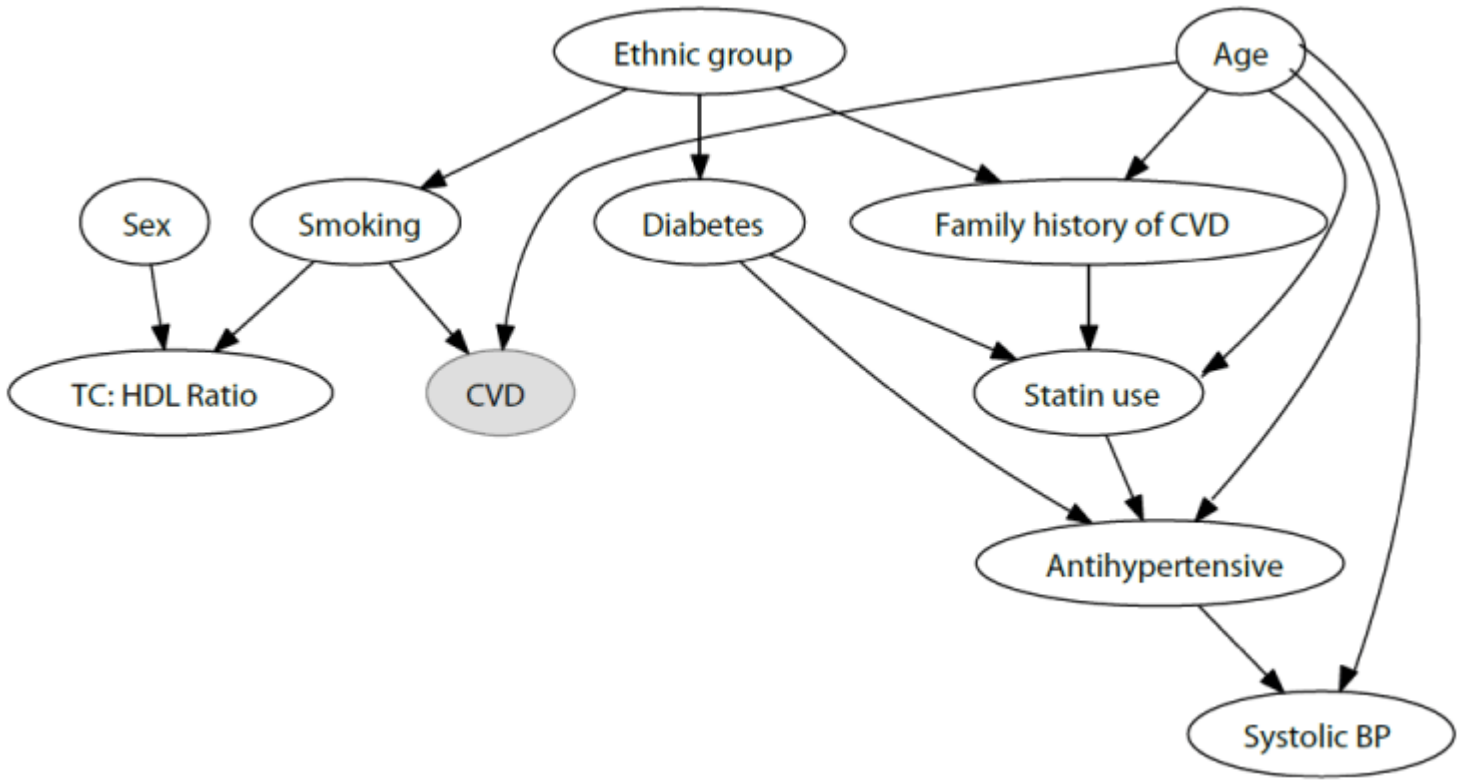
Finally, the actual values are these:

$$A = C = D = E = 1$$

$$B = 0$$

Hall (2007), p. 9

DAGS in Epidemiology



Thornley et al (2013), p. 4

So, how does this help with EV?

- Consider an RCT conducted to study the effect, Y, of treatment X, for every age group Z.
- The experimenters discover what the average treatment effect is for each age group.

DAG for Pearl’s Hypothetical Experiment

Variables:

- X = treatment (let’s say taking 1 pill)
- Y = effect (let’s say headache goes away)
- Z = age (at least in the first scenario)

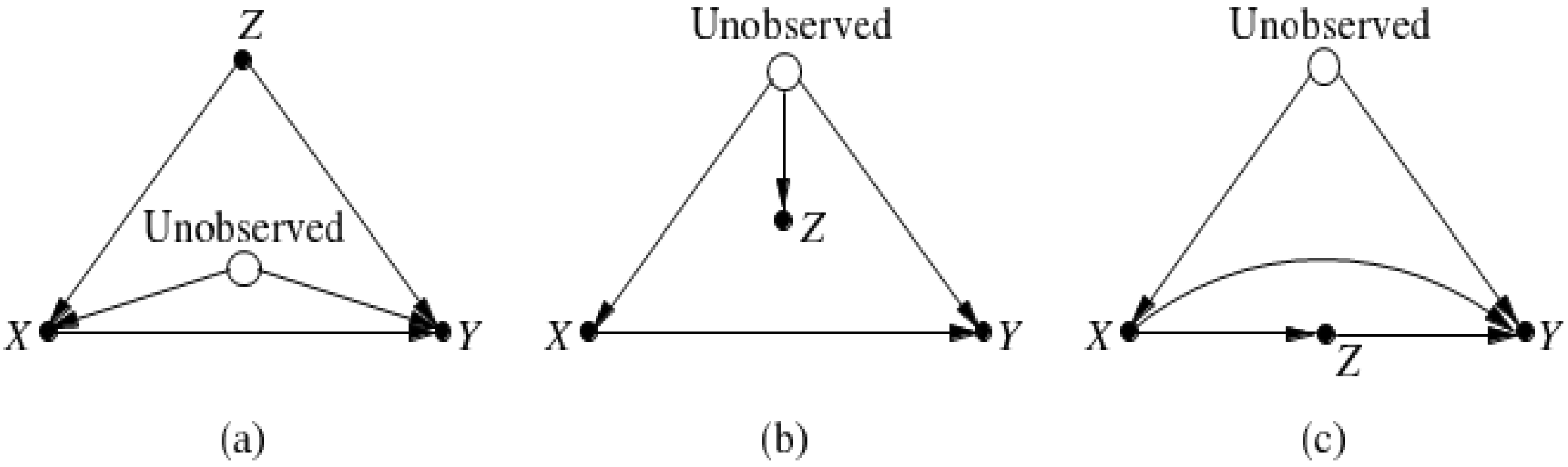
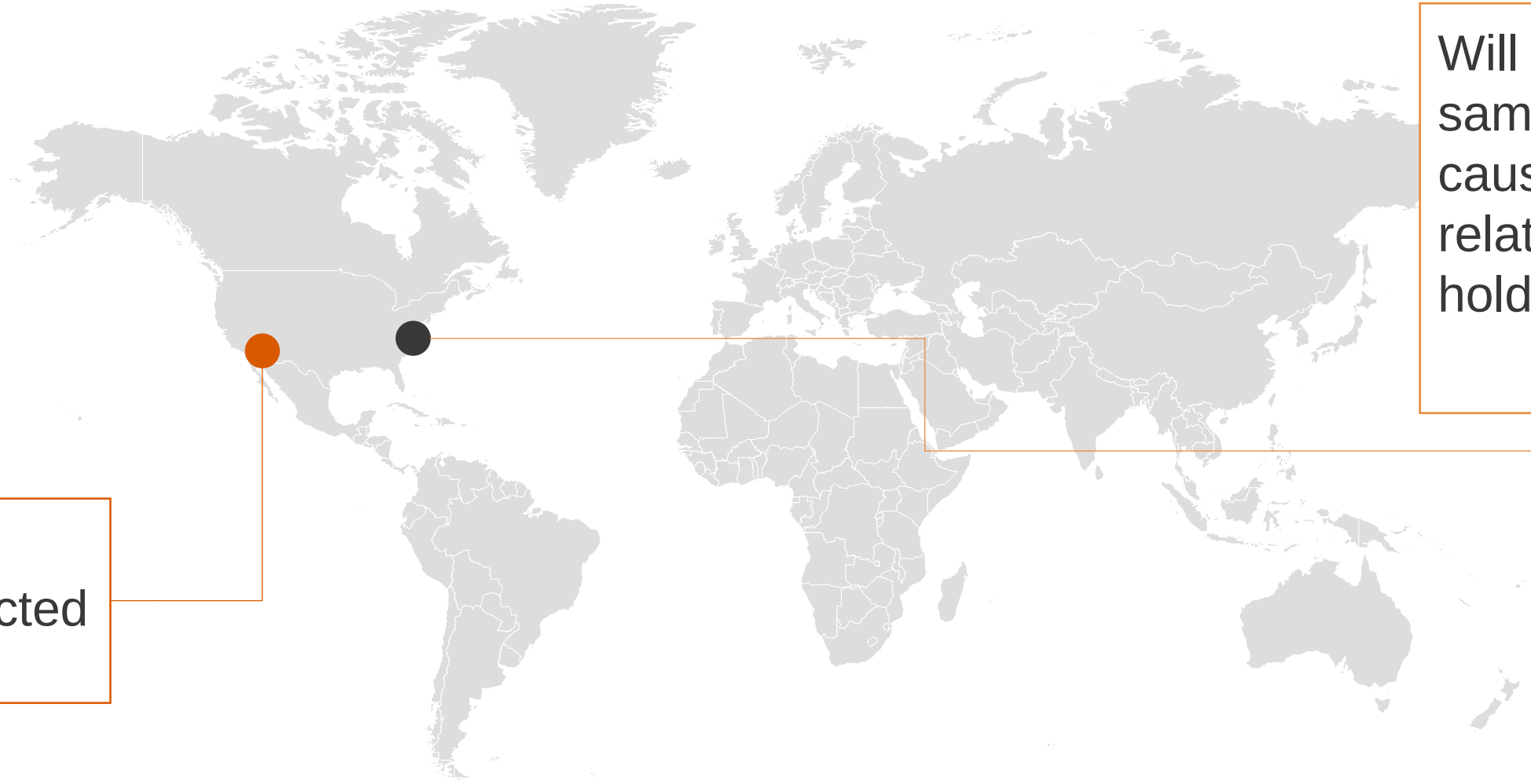


FIG. 3. Causal diagrams depicting Examples 1–3. In (a) Z represents “age.” In (b), Z represents “linguistic skills” while age (in hollow circle) is unmeasured. In (c), Z represents a biological marker situated between the treatment (X) and a disease (Y).

Pearl and Barenboim (2014), p. 584

Transportability of Causal Relationships



Will the same causal relationship hold here?

RCT Conducted here

DAG for Pearl's Hypothetical Experiment

- P(x,y,z) – Variable distribution in LA: describes the values of the Variables X, Y and Z in the experimental context
- P $*$(x,y,z) - Variable distribution in NYC (which is the environment we are curious about)
- How are we to estimate the causal effect of X on Y in NYC, given our knowledge of the results of the LA RCT and observational studies in NYC?

From Identification to Transportability

- Now we have a representation of the causal structure discovered in the experiment, the question becomes whether we can expect that structure to hold in the new context:

- According to P&B framework, what else do we need besides the DAG/SEM to decide on transportability?

What we need…

- ‘…licensing transportability requires knowledge of the mechanisms, or processes, through which population differences come about; different localization of these mechanisms yield different transport formulae.’

Pearl and Barenboim (2014), p. 586

Selection Variables and Selection Diagrams

- ‘Based on these observations, it is clear that if we are to represent formally the differences between populations (similarly, between experimental settings or environments), we must resort to a representation in which the causal mechanisms are explicitly encoded and in which differences in populations are represented as local modifications of those mechanisms.’

Pearl and Barenbom (2014), p.587

Selection Variables and Selection Diagrams

- ‘To this end, we will use causal diagrams augmented with a set, S, of “selection variables,” where each member of S corresponds to a mechanism by which the two populations differ, and switching between the two populations will be represented by conditioning on different values of these S variables.’

Pearl and Barenbom (2014), p.587

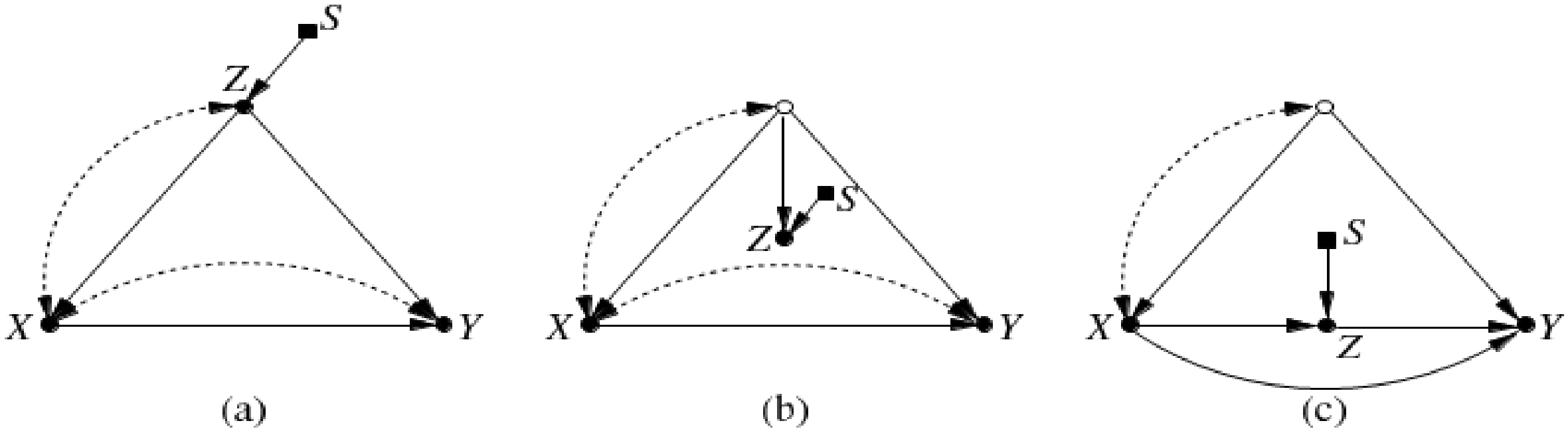


FIG. 4. Selection diagrams depicting specific versions of Examples 1–3. In (a), the two populations differ in age distributions. In (b), the populations differs in how Z depends on age (an unmeasured variable, represented by the hollow circle) and the age distributions are the same. In (c), the populations differ in how Z depends on X. In all diagrams, dashed arcs (e.g., X Y) represent the presence of latent variables affecting both X and Y.

Pearl and Barenboim (2014), p. 587

Selection Diagrams

- ‘… the S-variables locate the *mechanisms* where structural discrepancies between the two populations are suspected to take place. Alternatively, the absence of a selection node pointing to a variable represents the assumption that the mechanism responsible for assigning value to that variable is the same in the two populations.’

Pearl and Barenboim (2014), p. 588

Summary: P&B Advice to Experimenters

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- The selection diagram will guide your inference about what to expect in the new environment

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- Is this good advice?

Issue 1: Threats vs. Licensing Assumptions

- Threats = ‘explanations of what may go wrong when we try to transport results from one study to another while ignoring their differences.’

- ‘Rarely do we find an analysis of “licensing assumptions,” namely, formal conditions under which the transport of results across differing environments or populations is licensed from first principles.’

Pearl and Barenboim, (2014) p. 580

But S = threats

- ‘The selection variables in S may represent all factors by which populations may differ or that may “threaten” the transport of conclusions between populations.’

- So how does S-trapolation help us go beyond threats?

Pearl and Barenboim (2014), p. 587

Issue 2:The Problem with Mechanism

Causal mechanism:

"A causal mechanism is (i) a particular configuration of conditions and processes that (ii) always or normally leads from one set of conditions to an outcome (iii) through the properties and powers of the events and entities in the domain of concern."

The real question is: how do we get knowledge of mechanisms?

Little (2011), p.277

Extrapolator’s Circle

Daniel Steel in *Across the Boundaries: Extrapolation in Biology and Social Science* –

- ‘… extrapolation is worthwhile only when there are important limitations on what one can learn about the target by studying it directly. The challenge, then, is to explain how the suitability of the model as a basis for extrapolation can be established given only limited, partial information about the target.’

Steel Daniel (2008), p. 4

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- A version of Steel's extrapolator's circle:

Sources of information:

- 1) experimental result (which tells us about the causal relationship) and
- 2) observational studies in the new environment, which at most tell us about distribution of variables

- How do we glean knowledge of difference-producing mechanisms from these two sources?

The causal transporter’s circle?

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- But, in order to know that, I need to know about the mechanism responsible for the causal effect in the new environment.
- But if I knew that, why would I need to extrapolate from the experiment in the first place?

Assessment of S-trapolation as Sound Advice

- Next, a real life example of EV/transportation failure
- How does S-trapolation fare?

EV Failure: Bangladesh Integrated Nutrition Programme

An Example of EV Failure

- Cartwright's (2012) example of the difference in environment between India and Bangladesh
- Results in a successful intervention against child malnutrition in one environment (India) but not the other (Bangladesh).
- Let us say that 'M' is the 'treatment' variable, and it represents mother's level of education about nutrition.
- We intervene on 'M' by providing increased education about nutrition, and we hope that this leads to an increase in 'N', which is the variable representing child nutrition levels.

What would the DAG look like?

M → N

M = Mother education level

N = Child nutrition level

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- **Environmental discrepancy = control of family food budget**
- **S = Control of family budget**
- Where would S fit into the DAG?

What would the DAG look like?

S?

M → N

M = Mother education level

N = Child nutrition level

What S-trapolation ignores…

- **M -\→ N**
- **G → N**
- **G = senior adult responsible for buying food for family**

How can the advice be improved?

- Instead of S-trapolation, what other questions could be asked that could help experimenters decide whether a causal effect will hold in a new environment?

An Alternative Approach

- The Eco-systems approach

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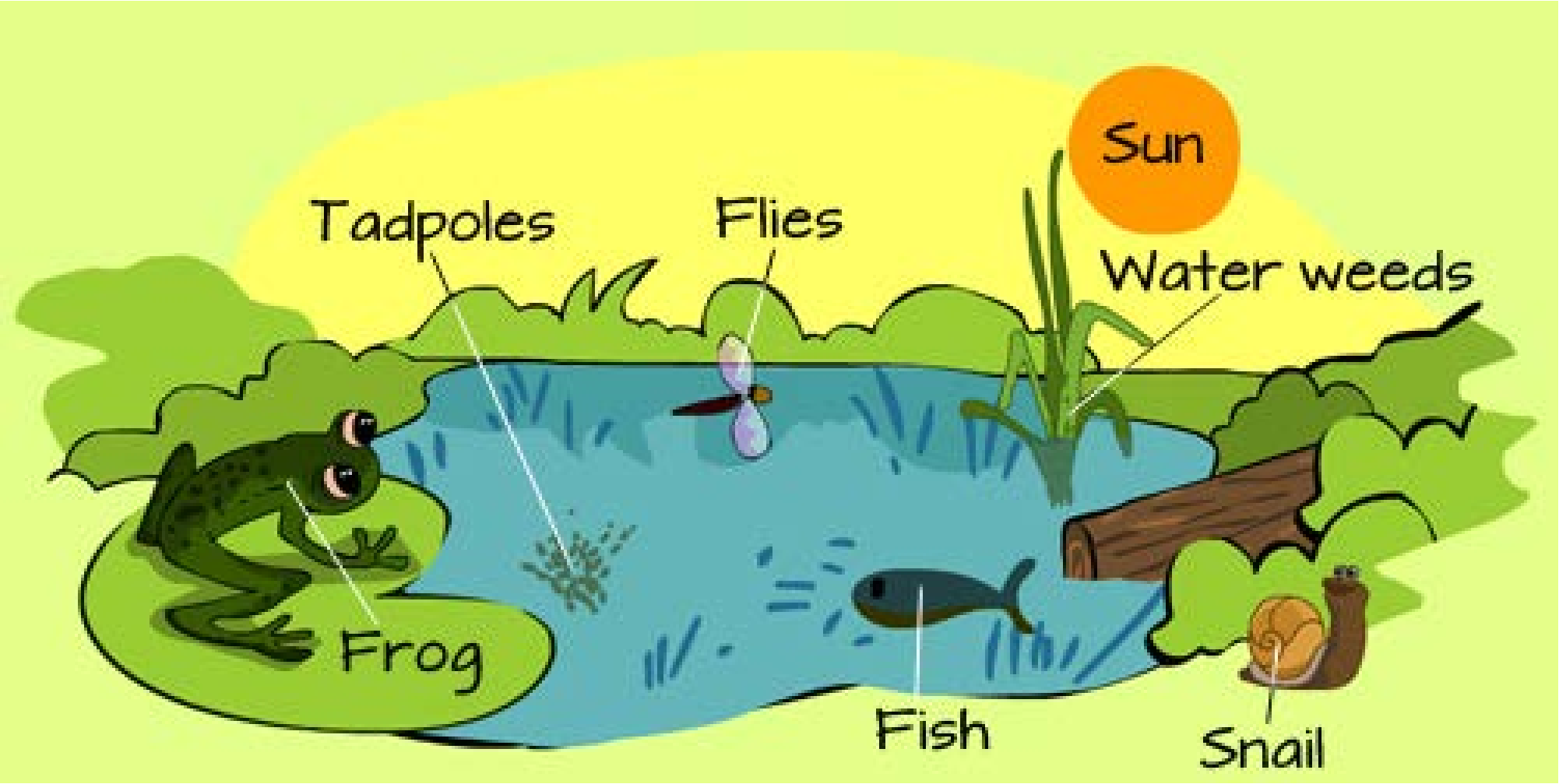
- What I propose: we should view causal relationships as analogous to the interactions between populations in an eco-system

A simple Eco-system



Eco-systems for Entrepreneurs

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- Now – the preferred method is to set up ecosystems that allow entrepreneurship to flourish.
- ‘How to Start an Entrepreneurial Revolution’ by Daniel J. Isenberg

Eco-systems for causal relationships

- Example 1: BINP
- What was it about the eco-system in India that allowed increased mother education to improve child nutrition?
- Can that same eco-system be expected to hold in Bangladesh?

Eco-systems for causal relationships

- Example 1: BINP

- No, because the role mother’s play in the Indian eco-system is played by mothers-in-law/fathers in Bangladesh.

- So – in the new eco-system, which population can best play the causally relevant role played by mothers in India?

Eco-systems for causal relationships

- Example 2: Class Sizes

- STAR school experiments in Tennessee – causal link between small class sizes and improved student performance

  => EV failure in other schools

- Rather ask: how did decreasing class sizes influence the classroom eco-system in well resourced schools?

- How would the same change influence the eco-system of the classroom in a poorly resourced school?

Eco-system Questions

- Definitely not as formal and rigorous as DAG/SEM
- But – provide solid and practical guidance to experimenters about what to look out for in new environments, especially for social/economic causes and effects

Summary

- DAG/SEMS provide a seemingly handy way of representing causal structure and identifying causal relationships

- P&B method for licensing transportation using S-variables doesn’t always yield the appropriate advice for making good EV/causal transport inference

- An alternative approach inspired by an analogy with eco-systems holds more promise for handling important problem cases.

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