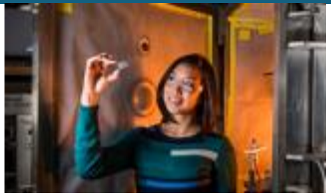
Sandia National Laboratories

Inference Using Causal Models



PRESENTED BY

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Causal Models as Data-Generating Processes

Causal models can be thought of as an "inference engine" taking inputs

- *Causal assumptions* and a structural model to encode these assumptions
- *Queries* about variables of interest and their relationships
- *Data* from observations (seeing) and interventions (doing)

… and producing outputs

- *Logical implications* of our assumptions
- *Statistical implications* of our assumptions
- *Claims* about the answers to our queries

Some examples of causal queries

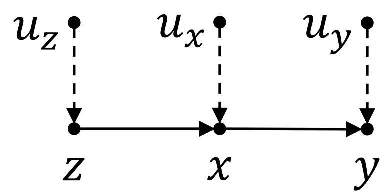
- Was it move/action X that led to winning/losing the game?
- Will a proposed policy on X have the intended results Y?
- How will the release of product X impact the sales of product Y?
- Does the evidence prove, beyond a shadow of a doubt, the crime Y was committed by X… Or was it an accident that would have happened anyway, because of Z?

Encoding the Structure of Causal Models

Structural Equations Models (SEMs)

- Variables of interest and their background factors
- Probability distributions over the background factors
- Functions that map from variables (and background factors) to variables
- Visually represented as a Directed Acyclic Graph (DAG)

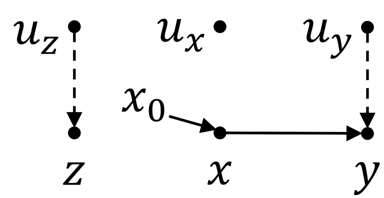
$$M\colon \begin{aligned} z &\Leftarrow f_Z(u_Z) \\ x &\Leftarrow f_X(z, u_X) \\ y &\Leftarrow f_Y(x, u_Y) \end{aligned}$$



Changes to the model can be reflected as changes in the graph

- Operations (e.g. interventions $do(x)$) add/remove edges

$$M_x\colon \begin{aligned} z &\Leftarrow f_Z(u_Z) \\ x &\Leftarrow x_0 \\ y &\Leftarrow f_Y(x, u_Y) \end{aligned}$$



$$P_M(y|do(x)) = P_{M_x}(y)$$

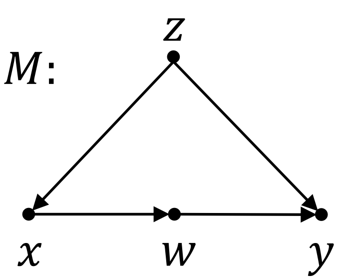
Inference using Causal Models

Many tools available for working with causal models

- D-separation, belief propagation, adjustment criteria and formulae, etc.
- Graphical representation supplements the discovery of solutions

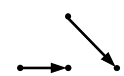
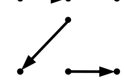
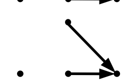
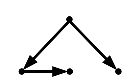
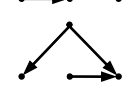
Variables: x = smoking, w = tar, y = cancer, z = genes (unobserved)

M:



$$z \Leftarrow f_Z(u_Z)$$
$$x \Leftarrow f_X(z, u_X)$$
$$w \Leftarrow f_W(x, u_W)$$
$$y \Leftarrow f_Y(w, z, u_Y)$$

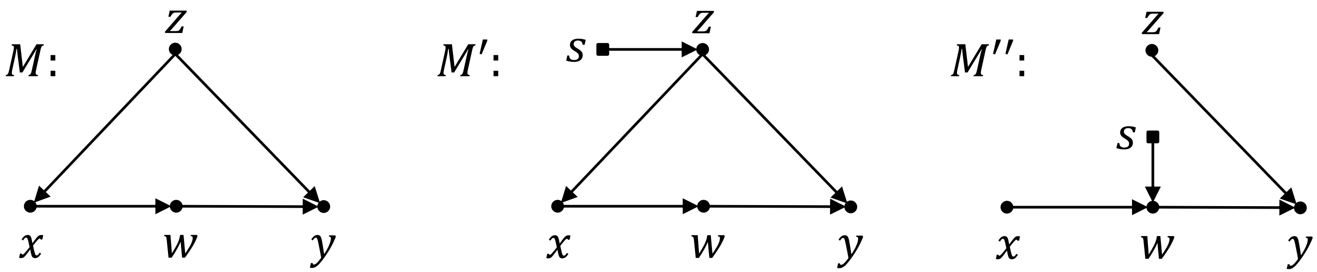
Query: $P(y|do(x))$

$= \Sigma_w P(y\|do(x), w) P(w\|do(x))$		Probability Axioms
$= \Sigma_w P(y\|do(x), do(w)) P(w\|do(x))$		Observation to Intervention
$= \Sigma_w P(y\|do(x), do(w)) P(w\|x)$		Intervention to Observation
$= \Sigma_w P(y\|do(w)) P(w\|x)$		Delete Intervention
$= \Sigma_{x'} \Sigma_w P(y\|do(w), x') P(x'\|do(w)) P(w\|x)$		Probability Axioms
$= \Sigma_{x'} \Sigma_w P(y\|w, x') P(x'\|do(w)) P(w\|x)$		Intervention to Observation
$= \Sigma_{x'} \Sigma_w P(y\|w, x') P(x') P(w\|x)$: Estimand		Delete Intervention

Selecting Between Causal Models

Selection diagrams identify where two domains of interest may differ

- E.g.: distribution of background factors, mapping functions, causal structure
- Represented graphically through selection variables (adding an edge $s_i \rightarrow v_i$)



$P(z) \neq P'(z)$ $\quad\quad$ $w \Leftarrow f(x) \neq f''(x)$

Example: Given studies in M', M'' how effective will marketing be in population M?

- Variables: x =advertisements, y = purchase, z = age, w = click-through rate
- Study in M' differs from target population in age
- Study in M'' was done as a randomized trial, and on a platform with high click-through rates

Transportability of Causal Models

Transportability allows us to make inferences between domains of interest

- Determine if generalizations are valid or invalid
- "License assumptions" about the transfer of causal relationships
- Different assumptions will yield different routes for transporting information
- Synthesize observational and interventional information from multiple domains

Some more examples highlighting transportability

- How do I navigate/find where I need to go when traveling in a new city?
- Why don't my physics simulations N match the new experimental measurements M?
- Should I have expected them to match in the first place?
- It's difficult to measure Y because of cost, what can I use as a proxy?
- Will a government program X in country N be effective if applied to country M?
- What experiments should be conducted to fill in the gaps of understanding?

Applications to Machine Learning and Artificial Intelligence

Dealing with data in a smarter way for machine learning

- How the data gets generated is important
- Model-based ML produces specific solutions to specific problems
- Combining human expertise in generating assumptions with ML methods for data analysis

Leveraging causal structure in AI agents

- Transfer learning during domain shift
- Sample efficiency and learning from counterfactuals
- Giving AI "free will"

References

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- Pearl, Judea. *Causality: Models, Reasoning, and Inference*, 2nd ed. Cambridge Univ. Press, 2009
- Pearl, Judea and Mackenzie, Dana. *The Book of Why: The New Science of Cause and Effect*, Basic Books, New York, 2018