Refutation of the Pearl model for cause-effect

Abstract: We evaluate the Pearl model for cause-effect in three edges as *not* tautologous. In fact, the representation is an abbreviated version of the four (or five) edge ontology used for axiom pinpointing which we refute elsewhere. What follows is that the claim of the seven tools in which causal methods are required is denied. These results form a *non* tautologous fragment of the universal logic VŁ4.

We assume the method and apparatus of Meth8/VŁ4 with Tautology as the designated proof value, **F** as contradiction, N as truthity (non-contingency), and C as falsity (contingency). The 16-valued truth table is row-major and horizontal, or repeating fragments of 128-tables, sometimes with table counts, for more variables. (See ersatz-systems.com.)

LET ~ Not, ¬ ; + Or, ∨, ∪, ⊔ ; - Not Or; & And, ∧, ∩, ⊓ , · , ⊗ ; \ Not And;
> Imply, greater than, →, ⇒ , ↦, ≻, ⊃, ↠ ; < Not Imply, less than, ∈, ≺, ⊂, ⊬, ⊭, ↞, ≲ ;
= Equivalent, ≡, :=, ⇔, ↔, ≙, ≈, ≃ ; @ Not Equivalent, ≠, ⊕;
% possibility, for one or some, ∃, ∃!, ◊, M; # necessity, for every or all, ∀, □, L;
(z=z) T as tautology, ⊤, ordinal 3; (z@z) **F** as contradiction, Ø, Null, ⊥ , zero;
(%z>#z) N as non-contingency, Δ, ordinal 1; (%z<#z) C as contingency, ∇, ordinal 2;
~(y < x) (x ≤ y), (x ⊆ y), (x ⊑ y); (A=B) (A~B).
Note for clarity, we usually distribute quantifiers onto each designated variable.

From: Char, S.; et al. (2020). Directions for explainable knowledge-enabled systems. arxiv.org/pdf/2003.07523.pdf

3. Directions

3.1. Causal Methods

In his widely-cited book .. , Pearl introduced a causal model for representing cause-effect relationships (Figure 2 [below]). This mathematical formulation of causality enabled researchers in fields, such as epidemiology and life sciences, to express causal structures .. . In addition, one of his recent technical reports .. abstracts his cause-effect model and presents an overview of the three-step knowledge hierarchy (Figure 3) of causality that is comprised of Association, Intervention, and Counterfactual knowledge .. . Pearl notes that current ML [machine language] techniques can address questions on Association knowledge (i.e., ... / Why am I being shown this answer? What else can I buy in addition to toothpaste?). In other words, Association knowledge contains correlations learned from associations. However, he adds that questions on Intervention knowledge require the system to understand and encode knowledge about the world besides just the data it is inferring a decision on. Finally, he states that Counterfactual questions that address the "but why not" question would need the system to be aware or understand the cause-effect relationships. We believe that this clear separation and identification of knowledge, in a hierarchical fashion, would allow AI systems to identify the components that would be necessary to generate explanations for these broad knowledge categories. While causal structures are desirable, it is generally hard to discover these models due to their dependence on human cognition. However, there have been approaches that mimic human reasoning and identify causal relationships from text .. through the leveraging of the semantics of causal mentions. These techniques look for words such as the ones listed in Pearl's report .. , including "cause," "allow," "preventing," "attributed to," "discriminating" and "should I". Further, in the same report .. , Pearl presents seven tools in which causal methods are required:

1. Encoding Causal Assumptions – Transparency and Testability
2. Do-calculus and the control of confounding

3. The Algorithmization of Counterfactuals
4. Mediation Analysis and the Assessment of Direct and Indirect Effects
5. Adaptability, External Validity, and Sample Selection Bias
6. Recovering from Missing Data
7. Causal Discovery

We believe that some of these tools, like Algorithmization of Counterfactuals, Causal Discovery, and Assessment of Direct and Indirect Effects, will be particularly useful to include in explanations that provide the users' causal justifications for the conclusions being recommended to them by the AI system.

In conclusion, we believe that causal representations will enable the ability of AI systems to address a broader class of explanations beyond the traditional "Why, What, and How" .. questions. Additionally, with a concrete, cause-effect graphical model, such as the one proposed by Pearl .. , the field has moved closer to a semantic representation of causality that may be used in a wide range of implemented systems. Such a semantic representation of causal structures in KGs [knowledge graphs] would lend to the development of causal, neuro-symbolic integrations.

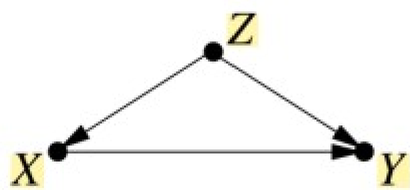

Figure 2. A representation of Pearl's cause-effect model [32,33] where $Q = P(Y|do(X))$, where X has an effect on Y and both depend on Z. Hence, he formulated the overall problem as a Bayesian equation in that $E_z = \sum_z P(Y|X,Z)P(Z)$. Pearl provides an intuitive example [32] of gender (Z) being a confounder on the effect that taking a drug (X) will have on recovery (Y). [Image is taken from [32] with permission from the author, Prof. Judea Pearl. [4]]

(3.1.2.1)

LET p, q, r: X, Y, Z.

(r>(q+(p>q)))>((r>q)=(r>(p>q))) ;

TTTT **F**TTT TTTT **F**TTT (3.1.2.2)

Remark 3.1.2.2: Eq. 3.1.2.2 as rendered is *not* tautologous, hence refuting the Pearl model of cause-effect. In fact, the representation is an abbreviated three-edge version of the four (or five) edge ontology used for axiom pinpointing which we refute elsewhere. What follows is that the seven tools in which causal methods are required is denied.