Counterfactual Causality from First Principles?[*]

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In this position paper we discuss three main shortcomings of existing approaches to counterfactual causality from the computer science perspective, and sketch lines of work to try and overcome these issues: (1) causality definitions should be driven by a set of precisely specified requirements rather than specific examples; (2) causality frameworks should support system dynamics; (3) causality analysis should have a well-understood behavior in presence of abstraction.

1 Introduction

Counterfactual reasoning has multiple applications to forensic analysis of failures in safety-critical systems. Modern embedded and cyber-physical systems are characterized by a large number of concurrent components with multiple interactions between them. Furthermore, physical environment of such systems adds to the complexity of dynamics of system executions, and some of the physical interactions may not be directly observable. Consider an example from the medical domain [28]. A patient is being treated for pain using a medication delivered by an infusion pump. To prevent overdoses, which can be fatal, the system is equipped with a safety interlock that stops the pump if a dangerous condition is detected through vital sign sensors, such as blood oxygenation and pulse rate. If an overdose occurs, causality analysis faces several challenges. The pump may be infusing medication at a slightly higher rate than programmed, but was it the cause? Infusion is a continuous process, and duration of the infusion is just as important factor as the infusion rate. Proper abstraction of such an interaction is important for the analysis. Similarly, the interlock may not have detected the overdose symptoms in time, but was it the problem of the algorithm used by the interlock or the fact that the patient had unusually high sensitivity to the drug. Complex dynamics of the physiological effects of pain medication need to be taken into account, since they directly affect how quickly the patient gets overdosed.

In the rest of this paper, we present three research directions in counterfactual causality analysis that may help, in the future, to address challenges posed by this motivating example. First, we argue that causality definitions should be driven not by individual examples but by a set of precisely specified requirements and discuss what these requirements may include. Second, we argue that support for system dynamics and temporal relationships should be included in the causality framework. Note that, by themselves, the techniques discussed may not be sufficient to incorporate continuous dynamics that the example needs. However, the third research direction deals with the use of abstractions in causality analysis. Such abstraction techniques as discretization of continuous signals may allow us to eventually handle the full complexity of causality analysis in cyber-physical systems.

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2 Escaping the TEGAR

Research on counterfactual causality analysis has been marked, since its early days [19], by a succession of definitions of causality that are informally (in)validated against human intuition on mostly simple examples. Let us call this approach TEGAR, *textbook example guided analysis refinement*. TEGAR contrasts with mathematics and natural sciences building knowledge on theorems and proofs, in that most work on causation lacks formal properties against which the definitions are tested. As a result, TEGAR suffers, as pointed out in [10], from its dependence on the tiny number and incompleteness of examples in the literature and the lack of stability of the intuitive judgments against which the definitions are validated. This absence of formal tools for evaluating theories of causation is not primarily owed to a lack of formalization: at least since the works of [33, 29], different formal definitions of causality have been proposed. Among the most influential definitions of counterfactual causality are Lewis' possible world semantics [24, 25, 26] and Pearl's and Halpern's actual causality [29, 17, 15]. Both definitions have undergone a series of refinements in order to match human intuition on additional examples that were proposed to challenge them. One may doubt that this is the end of the story. It is interesting to note that the understanding of causality and explanations in natural sciences faces a similar lack of objective referential, as witnessed by the dispute reedited in [36].

We believe that a more constructive, reproducible approach to design definitions of counterfactual causality is needed. A first step towards this goal would be to formally define a family of requirements — that are as agnostic as possible of concrete models of computation — on counterfactual causality, rather than a mere set of competing concrete definitions.

Some efforts to axiomatize counterfactual reasoning have been made. On structural equations models [29] (SEM), [9] introduces three properties that hold in all (recursive and nonrecursive) SEM, two of which characterize manipulation (Pearl's *do* operator) in the recursive case. [14] generalizes these results to an axiomatic characterization of the classes of non-recursive SEM with unique solutions, and arbitrary SEM. With the goal of using counterfactual causality for fault ascription — that is, blaming a system failure on one or more component faults —, [13] proposes general constraints on counterfactuals that are sufficient to entail correctness and completeness. Similarly, a general definition of actual causality is proposed and then instantiated in [2]. While none of these axiom systems is strong enough to characterize more than basic properties of counterfactual reasoning, we believe that there is still room for progress.

Let us have a closer look why current accounts of counterfactual causality are not satisfactory. The impact of modeling choices on counterfactual analysis has long been recognized, see for instance [16]. In our eyes, one of the most critical shortcomings of state-of-the-art SEM-based approaches is the dependence of the result on the structure of the model.

Example 1 (Lamp [37]) *Consider three variables A, B, C ranging over $\{-1,0,1\}$. Lamp L_1 is on whenever any two of the variables share the same value. Lamp L_2 is on whether there is a value among $\{-1,0,1\}$ that is different from the values of all three variables. The structural equations are as follows:*

$$\begin{aligned} L_1 &= (A = B \lor B = C \lor A = C) \\ L_2 &= (N_{-1} \lor N_0 \lor N_1) \quad \textit{where} \\ N_i &= (A \neq i \land B \neq i \land C \neq i), \quad i \in \{-1,0,1\} \end{aligned}$$

In the actual world, the state is $A = 1$, $B = C = -1$, $N_{-1} = 0$, $N_0 = 1$, $N_1 = 0$, and $L_1 = L_2 = 1$. Halpern's modified definition of actual causality [15] considers each of $B = -1$ and $C = -1$ as a cause of $L_1 = 1$

and of $L_2 = 1$. However, it also considers $A = 1$ as a cause of $L_2 = 1$.[1] *Intuitively, this is due to the fact that there is a contingency — namely, holding N_1 at zero — under which switching A from 1 to 0 switches off L_2. Thus, the resulting causes for $L_1 = 1$ and $L_2 = 1$ differ even though the definitions of L_1 and L_2 are logically equivalent.*

This example brings us to a first set of points we want to make.

First, the result of causality analysis should depend on the semantics of the model but not its syntax. An intuitive motivation for this requirement is that the analysis should be "objective enough" so as to determine causality independently of how the story is told. More importantly, the formal motivation is that searching for a theory of causation that allows us to reason about equivalence and refinement of models is hopeless as long as semantically equivalent models are distinguishable.

Second, we need formalization of counterfactual causality based on *first principles*, similar to the approach of [30], in the sense that the formalization is constructed from general requirements. As in the design processes in most engineering disciplines, the development of a definition of causation should be performed top-down, starting from the question of *what formal requirements the definition should meet*, independently of concrete modeling frameworks. An example of such requirements is robustness of causation under equivalence of models, for a given definition of equivalence. Directly focusing on the question "how to implement it?" is likely to narrow down the design space prematurely and require "debugging" of the definitions, as discussed above. In turn, such a "specification" of counterfactual causality should help us in answering questions such as:

- How to design a counterfactual analysis satisfying the requirements?
- Can we obtain the same analysis result with other tools than counterfactual analysis? What are properties of interest that are satisfied only by counterfactual analysis?
- Is counterfactual causality analysis inherently NP-complete (as Halpern and Pearl's actual causality) [8, 15]?

3 Native Support for System Dynamics

It has been pointed out in [10] that Halpern and Pearl's definitions of actual causality, based on SEM over propositions, poorly support reasoning about state changes. Other limitations of SEM — in particular, their inability to distinguish between states and events, and between presence and absence of an event — have also been noted e.g. by Hopkins and Pearl [18], and several other formalisms have been suggested for supporting reasoning about causal ascription (see for instance [5]). Counterfactual definitions of necessary causality for behaviors over time have been proposed for biochemical reactions in [6] and similarly for programs in [7], and for fault ascription in component-based systems in [12]; some works define variants of actual causality on models of execution traces [4, 21].

Apart from the modeling infelicities of SEM, a key point is that models that allow finitary descriptions of systems dynamics are essential for conducting actual cause analysis. In particular since counterfactual executions may be unbounded it may be necessary to explore a prefix of the counterfactuals whose length is not bounded a priori, in order to evaluate the property. For instance, a system dynamics can be represented by a set of traces or some sort of automata, and actual cause analysis for a property violation during some execution can consist in constructing sets of traces or automata executions that

[1] The previous definitions of actual causality [29, 17] consider each of $A = 1, B = -1, C = -1$ as a cause of both $L_1 = 1$ and $L_2 = 1$.

avoid a particular set of violating states but keep at least the antecedent part of the original execution. In order to effectively construct and analyze these counterfactual executions, we then need a symbolic representation, along with symbolic formulations of the counterfactual construction and analysis. Symbolic approaches to causality checking have been proposed e.g. in [3] for Halpern and Pearl's actual causality and in [35, 11] for fault ascription in real-time systems; except for [11] they rely on generating and analyzing bounded counterfactuals.

For systems dynamics, the notion of coalgebra [20, 31] provides a systematic setting, generalizing notions of transition systems that include e.g. many variants of probabilistic and stochastic transition systems [32], as well as hybrid transition systems [27]. Following the (hyper)set-based formulation of [1], a system can be described coalgebraically as a possibly infinite, mutually recursive, set of equations of the form $x = F(x)$, where F is some operator on sets, and x some variable. For instance, the standard notion of (finitely branching) labelled transition system is given by operator F defined as $F(X) = \mathcal{P}_f(A \times X)$ where $\mathcal{P}_f(S)$ denotes the set of finite subsets of some set S, X is the set of (state) variables and A is the set of labels. One benefit of the coalgebraic approach is its generality. For instance, many different variants of transition systems, including timed, quantitative, and stochastic ones, are instances of coalgebras. Our contention is that it could be beneficial to develop causality analysis in an abstract coalgebraic framework, if only to identify abstractions and constructions (e.g. for counterfactuals) that apply generally irrespective of the actual details of the chosen operators. [13] provides an example of counterfactual analysis developed in an abstract setting – that of configuration structures, which can be understood as a general model for concurrent system executions or unfoldings. It seems to us that general notions of causality and counterfactuals should not depend on the specifics of system or transition system models. Rather, we expect that at least general constraints on counterfactual construction and causal dependencies can be obtained for abstract system models and properties. For instance, a general notion of behavior and bisimulation can be defined for coalgebraic systems [20, 31], that does not depend on the specifics of the chosen operator. Obtaining similarly abstract characterizations of causal dependencies or counterfactuals would be of enormous benefit.

Once we allow for unbounded executions also in the actual world — that is, the observed execution, — *incremental* causality analysis becomes an issue. Many causality analysis techniques operate on the observed prefix of the execution at the point when an event of interest, such as a failure, is discovered. If the analysis relies on explicit construction of counterfactuals, there is a danger of repeating the same work for different counterfactuals. Moreover, if the analysis has to be performed multiple times over an evolving execution, redundant efforts are even more likely. In this case, incremental analysis can keep partially constructed counterfactuals, hopefully in a symbolic form, and update them as the next observation from the execution arrives. While this approach may not reduce complexity of causality analysis, it may amortize the cost over a long-running execution and reduce analysis latency, once an event of interest is observed.

With this vision, the partial, evolving counterfactual would allow us to answer the question, "if the event of interest is to happen in the next step, what would the causes be?" When there are multiple events of interest — for instance, multiple ways for a failure to occur, — the danger is that the incremental analysis would incur additional cost with bookkeeping for events that never occur.

4 Causation and Abstraction

Important applications of causality analysis include the construction of concise explanations for observed behaviors [4, 6], and establishing liability [23]. Preconditions for causality analyses to be applicable and sound are (a) availability of the necessary observations to determine causality, and (b) consistency between the model on which the analysis is performed, and the implementation generating the observations. Requirement (a) is addressed by ensuring *accountability* [22] with respect to causality analysis, that is, constructing systems in such a way that all information necessary to elucidate the causes of events of interest is logged. We believe that accountability with respect to causality analysis should become a design requirement for new designs of safety-critical systems.

Surprisingly, requirement (b) has received little attention in the computer science community so far. However, using counterfactual analysis on hand-crafted models of causal dependencies to determine the causes of a system failure is much like modeling a critical system in one formalism and then implementing it in another one from scratch — the semantic gap between the model and the actual system makes it difficult to ensure that the former is faithful with respect to the latter. Software design has been formalized as a series of refinements from a high-level specification down to the implementation; for the design of cyber-physical systems, numerous discrete abstractions of the continuous dynamics have been proposed, see e.g. [34]. Theories of causation should therefore be able to track causation through these levels of abstraction and refinement, for instance, to verify causation on a small abstract model and then refine potential causes identified on that level. To this end, theories of causation should have a well-defined behavior under abstraction and refinement, such as correctness (any cause in the abstract model is refined into a cause in the refinement) or completeness (the abstraction of any cause in the refinement is also a cause in the abstract model) of abstraction. One can go even further and ask how causality meshes with system equivalences. The standard benchmark for system equivalences is contextual equivalence: given some notion of observable and some notion of system execution, two systems are equivalent when, placed in the same context, they have the same observables and the same executions. It seems to us plausible to ask of a notion of causality to be robust with respect to contextual equivalence: if causal analysis in a complex system $S[A]$, where $S[\cdot]$ is a context for subsystem A, yields a certain result, then the same analysis performed on $S[B]$, where B is contextually equivalent to A, should yield the same result (e.g. pinpointing some observable event in A or B as the actual cause of some property violation). We are not aware of any work studying abstraction, refinement, or robustness, in the SEM framework.

Finally, deriving an implementation by refining an abstract specification usually implies that the abstract model encompasses some non-determinism. In order to support multiple levels of refinement, theories of causation have to be able to cope with this non-determinism.

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