From C-Believed Propositions to the Causal Calculator

VLADIMIR LIFSCHITZ

1 Introduction

Default rules, unlike inference rules of classical logic, allow us to derive a new conclusion only when it does not conflict with the other available information. The best known example is the so-called commonsense law of inertia: in the absence of information to the contrary, properties of the world can be presumed to be the same as they were in the past. Making the idea of commonsense inertia precise is known as the frame problem [Shanahan 1997]. Default reasoning is nonmonotonic, in the sense that we may be forced to retract a conclusion derived using a default when additional information becomes available.

The idea of a default first attracted the attention of AI researchers in the 1970s. Developing a formal semantics of defaults turned out to be a difficult task. For instance, the attempt to describe commonsense inertia in terms of circumscription outlined in [McCarthy 1986] was unsatisfactory, as we learned from the Yale Shooting example [Hanks and McDermott 1987].

In this note, we trace the line of work on the semantics of defaults that started with Judea Pearl's 1988 paper on the difference between "E-believed" and "Cbelieved" propositions. That paper has led other researchers first to the invention of several theories of nonmonotonic causal reasoning, then to designing action languages C and C+, and then to the creation of the Causal Calculator—a software system for automated reasoning about action and change.

2 Starting Point: Labels E and C

The paper *Embracing Causality in Default Reasoning* [Pearl 1988] begins with the observation that

almost every default rule falls into one of two categories: expectationevoking or explanation-evoking. The former describes association among events in the outside world (e.g., fire is typically accompanied by smoke); the latter describes how we reason about the world (e.g., smoke normally suggests fire).

Thus the rule fire \Rightarrow smoke is an expectation-evoking, or "causal" default; the rule smoke \Rightarrow fire is explanation-evoking, or "evidential." To take another example,

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(1) rained \Rightarrow grass_wet

is a causal default;

(2) grass_wet \Rightarrow sprinkler_on

is an evidential default.

To discuss the distinction between properties of causal and evidential defaults, Pearl labels believed propositions by distinguishing symbols C and E. A proposition P is E-believed, written E(P), if it is a direct consequence of some evidential rule. Otherwise, if P can be established as a direct consequence of only causal rules, it is said to be C-believed, written C(P). The labels are used to prevent certain types of inference chains; in particular, C-believed propositions are prevented in Pearl's paper from triggering evidential defaults. For example, both causal rule (1) and evidential rule (2) are reasonable, but using them to infer sprinkler_on from rained is not.

We will see that the idea of using the distinguishing symbols C and E had a significant effect on the study of commonsense reasoning over the next twenty years.

3 "Explained" as a Modal Operator

The story continues with Hector Geffner's proposal to turn the label C into a modal operator and to treat Pearl's causal rules as formulas of modal logic. A formula F is considered "explained" if the formula CF holds.

A rule such as "rain causes the grass to be wet" may thus be expressed as a sentence

 $\texttt{rain} \to C\,\texttt{grass_wet},$

which can then be read as saying that if rain is true, grass_wet is explained [Geffner 1990].

The paper defined, for a set of axioms of this kind, which propositions are "causally entailed" by it.

Geffner showed how this modal language can be used to describe effects of actions. We can express that e(x) is an effect of an action a(x) with precondition p(x) by the axiom

(3) $p(x)_t \wedge a(x)_t \to \mathsf{C}e(x)_{t+1},$

where $p(x)_t$ expresses that fluent p(x) holds at time t, and $e(x)_{t+1}$ is understood in a similar way; $a(x)_t$ expresses that action a(x) is executed between times t and t+1.

Such axioms explain the value of a fluent at some point in time (t + 1) in the consequent of the implication) in terms of the past (t in the antecedent). Geffner gives also an example of explaining the value of a fluent in terms of the values of other fluents at the same point in time: if all ducts are blocked at time t, that causes

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the room to be stuffy at time t. Such "static" causal dependencies are instrumental when actions with indirect effects are involved. For instance, blocking a duct can indirectly cause the room to become stuffy. We will see another example of this kind in the next section.

4 Predicate "Caused"

Fangzhen Lin showed a few years later that the intuitions explored by Pearl and Geffner can be made precise without introducing a new nonmonotonic semantics. Circumscription [McCarthy 1986] will do if we employ, instead of the modal operator C, a new predicate.

Technically, we introduce a new ternary predicate *Caused* into the situation calculus: Caused(p, v, s) if the proposition p is caused (by something unspecified) to have the truth value v in the state s [Lin 1995].

The counterpart of formula (3) in this language is

(4) $p(x,s) \rightarrow Caused(e(x), true, do(a(x), s)).$

Lin acknowledges his intellectual debt to [Pearl 1988] by noting that his approach echoes the theme of Pearl's paper—the need for a primitive notion of causality in default reasoning.

The proposal to circumscribe *Caused* was a major event in the history of research on the use of circumscription for solving the frame problem. As we mentioned before, the original method [McCarthy 1986] turned out to be unsatisfactory; the improvement described in [Haugh 1987; Lifschitz 1987] is only applicable when actions have no indirect effects. The method of [Lin 1995] is free of this limitation. The main example of that paper is a suitcase with two locks and a spring loaded mechanism that opens the suitcase instantaneously when both locks are in the up position; opening the suitcase may thus become an indirect effect of toggling a switch. The static causal relationship between the fluents up(l) and *open* is expressed in Lin's language by the axiom

(5) $up(L1, s) \land up(L2, s) \rightarrow Caused(open, true, s).$

5 Principle of Universal Causation

Yet another important modification of Geffner's theory was proposed in [McCain and Turner 1997]. That approach was originally limited to formulas of the form

 $F \to \mathsf{C}G,$

where F and G do not contain C. (Such formulas are particularly useful; for instance, (3) has this form.) The authors wrote such a formula as

(6) $F \Rightarrow G$,

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so that the thick arrow \Rightarrow represented in their paper a combination of material implication \rightarrow with the modal operator C. In [Turner 1999], that method was extended to the full language of [Geffner 1990].

The key idea of this theory of causal knowledge is described in [McCain and Turner 1997] as follows:

Intuitively, in a causally possible world history every fact that is caused obtains. We assume in addition the *principle of universal causation*, according to which—in a causally possible world history—every fact that obtains is caused. In sum, we say that a world history is causally possible if exactly the facts that obtain in it are caused in it.

The authors note that the principle of universal causation represents a strong philosophical commitment that is rewarded by the mathematical simplicity of the nonmonotonic semantics that it leads to. The definition of their semantics is indeed surprisingly simple, or at least short. They note also that in applications this strong commitment can be easily relaxed.

The extension of [McCain and Turner 1997] described in [Giunchiglia, Lee, Lifschitz, McCain, and Turner 2004] allows F and G in (6) to be slightly more general than propositional formulas, which is convenient when non-Boolean fluents are involved. In the language of that paper we can write, for instance,

(7) $a_t \Rightarrow f_{t+1} = v$

to express that executing action a causes fluent f to take value v.

6 Action Descriptions

An action description is a formal expression representing a transition system—a directed graph such that its vertices can be interpreted as states of the world, with edges corresponding to the transitions caused by the execution of actions. In [Giunchiglia and Lifschitz 1998], the nonmonotonic causal logic from [McCain and Turner 1997] was used to define an action description language, called C. The language C+ [Giunchiglia, Lee, Lifschitz, McCain, and Turner 2004] is an extension of C that accomodates non-Boolean fluents and is also more expressive in some other ways.

The distinguishing syntactic feature of action description languages is that they do not involve symbols for time instants. For example, the counterpart of (7) in C+ is

a causes f = v.

The C+ keyword **causes** implicitly indicates a shift from the time instant t when the execution of action a begins to the next time instant t+1 when fluent f is evaluated. This keyword represents a combination of three elements: material implication, the Pearl-Geffner causal operator, and time shift.

7 The Causal Calculator

Literal completion, defined in [McCain and Turner 1997], is a modification of the completion process familiar from logic programming [Clark 1978]. It is applicable to any finite set T of causal laws (6) whose heads G are literals, and produces a set of propositional formulas such that its models in the sense of propositional logic are identical to the models of T in the sense of the McCain-Turner causal logic. Literal completion can be used to reduce some computational problems involving C action descriptions to the propositional satisfiability problem.

This idea is used in the design of the Causal Calculator (CCALC)—a software system that reasons about actions in domains described in a subset of C [McCain 1997]. CCALC performs search by invoking a SAT solver in the spirit of the "planning as satisfiability" method of [Kautz and Selman 1992]. Version 2 of CCALC [Lee 2005] extends it to C+ action descriptions.

The Causal Calculator has been succesfully applied to several challenge problems in the theory of commonsense reasoning [Lifschitz, McCain, Remolina, and Tacchella 2000], [Lifschitz 2000], [Akman, Erdoğan, Lee, Lifschitz, and Turner 2004]. More recently, it was used for the executable specification of norm-governed computational societies [Artikis, Sergot, and Pitt 2009] and for the automatic analysis of business processes under authorization constraints [Armando, Giunchiglia, and Ponta 2009].

8 Conclusion

As we have seen, Judea Pearl's idea of labeling the propositions that are derived using causal rules has suggested to Geffner, Lin and others that the condition

G is caused (by something unspecified) if F holds

can be sometimes used as an approximation to

G is caused by F.

Eliminating the binary "is caused by" in favor of the unary "is caused" turned out to be a remarkably useful technical device.

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