Back to the Future: Changing the Direction of Time for the Discovery of Causality

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Abstract. In this paper we present the idea of using the direction of time to discover causality in temporal data. The Temporal Investigation Method for Enregistered Record Sequences (TIMERS), creates temporal classification rules from the input, and then measures the accuracy of the rules. It does so two times, each time assuming a different direction for time. The direction that results in rules with higher accuracy determines the nature of the relation. For causality, TIMERS assumes the natural direction of time, which states that events in the past can cause a target event in the present time. For the acausality test, TIMERS assumes a backward flow of time, which states that events in the future can cause a target event in the present. There is a third alternative, and that is an instantaneous relation, where events in the present occur at the same time as a target event, at the same time.

1. Forward and Backward Directions of Time

We consider a set of rules to define a relationship among the condition attributes and the decision attribute. A temporal rule is one that involves variables from times different than the decision attribute's time of observation. An example temporal rule is:

If {(At time T_{-3}: $x = 2$) **and** (At time T_{-1}: $y > 1$, $x = 2$)} **then** (At time T: $x = 5$). (Rule 1).

This rule indicates that the current value of x (at time T) depends on the value of x, 3 time steps ago, and also on the value of x and y, 1 time step ago. We use a preprocessing technique called *flattening* to change the input data into a suitable form for extracting temporal rules with tools that are not based on an explicit representation of time. With flattening, data from consecutive time steps are put into the same record, so if in two consecutive time steps we have observed the values of x and y as: Time n: $<x = 1, y = 2>$, Time $n + 1$: $<x = 3, y = 2>$, then we can flatten these two records to obtain <Time $T - 1$: $x_1 = 1$, $y_1 = 2$, Time T: $x_2 = 3$, $y_2 = 2$>. The "Time <number>" keywords are implied, and do not appear in the records. The initial temporal order of the records is lost in the flattened records, and time always starts from $(T - w - 1)$ inside each flattened record, and goes on until T. Time T signifies the "current time" which is relative to the start of each record. Such a record can be used to predict the value of either x_2 or y_2 using the other attributes. Since we refrain from using any condition attribute from the current time, we modify the previous record by omitting either x_2 or y_2.

In the previous example we used *forward flattening*, because the data is flattened in the same direction as the forward flow of time. We used the previous observations to predict the value of the decision attribute. The other way to flatten the data is *backward flattening*, which goes against the natural flow of time. Given the two previous example records, the result of a backward flattening would be < Time T: $y_1 = 2$, Time $T + 1$: $x_2 = 3$, $y_2 = 2$>. Inside the record, time starts at T, and ends at $(T + w - 1)$. This record could be used to predict the value of y_1 based on the other attributes. x_1 is omitted because it appears at the same time as the decision attribute y_1. In the backward direction, *future* observations are used to predict the value of the decision attribute.

There is no consensus on the definitions of terms like causality or acausality. For this reason we provide our own definitions here.

1.1 Instantaneous. An *instantaneous* set of rules is one in which the current value of the decision attribute in each rule is determined solely by the current values of the condition attributes in each rule. An instantaneous set of rules is an *atemporal* one. Another name for an instantaneous set of rules is a (atemporal) *co-occurrence*, where the values of the decision attribute are associated with the values of the condition attributes.

Instantaneous definition: For any rule r in rule set R, if the decision attribute d appears at time T, then all condition attributes should also appear at time T.

1.2 Causal. In a *causal* set of rules, the current value of the decision attribute relies only on the previous values of the condition attributes in each rule.

Causal definition: For any rule r in the rule set R, if the decision attribute d appears at time T, then all condition attributes should appear at time $t < T$.

1.3 Acausal. In an *acausal* set of rules, the current value of the decision attribute relies only on the future values of the condition attributes in each rule.

Acausal definition: For any rule r in the rule set R, if the decision attribute d appears at time T, then all condition attributes should appear at time $t > T$.

All rules in a causal rule set have the same direction of time, and there are no attributes from the same time as the decision attribute. This property is guaranteed simply by not using condition attributes from the same time step as the decision attribute, and also by sorting the condition attributes in an increasing temporal order, until we get to the decision attribute. The same property holds for acausal rule sets, where time flows backward in all rules till we get to the decision attribute. Complementarily, in an instantaneous rule set, no condition attribute from other times can ever appear. The TIMERS methodology guarantees that all the rules in the rule set inherit the property of the rule set in being causal, acausal, or instantaneous.

More information about the TIMERS method can be found in the following papers, both by Kamran Karimi and Howard J. Hamilton. "Using TimeSleuth for Discovering Temporal/Causal Rules: A Comparison," In Proceedings of the Sixteenth Canadian Artificial Intelligence Conference (AI'2003), Halifax, NS, Canada, June 2003. And ``Distinguishing Causal and Acausal Temporal Relations," In Proceedings of the Seventh Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD'2003), Seoul, South Korea, April/May 2003.