CAUSE AND EFFECT RELATIONSHIPS II

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The chapter “AGI: CAUSALITY“ discussed ways to find causal relationships.The subject of discussion in this chapter is the difference between causal relationships and related concepts. Understanding these differences allows for understanding the situation in this area better.

PROBABILISTIC MODELS vs. CAUSATION

Let us imagine such a situation in the spirit of cinematic thrillers: a particular intruder will get into someone else's basement and set up surveillance when the light is turned on there. Watching the curtained window, he gathered statistics: out of several hundred times when the light was on, not one falls between midnight and 6 in the morning. What is the probability that it will be dark when he enters the basement at 2 am? The answer is obvious, isn't it?

Such a task looks typical for AI systems that use statistical decision-making methods. Within the framework of this approach, the apparent answer to the question posed above is the assertion that the required probability is close to zero. Meanwhile, a villain using this approach breaks into the basement in the middle of the night - and discovers that the lights will turn on automatically if there is a moving object in the basement. When penetrating the basement, the actual probability that there will be light there is close to **1,** regardless of the penetration time. Expectations based on observational statistics and reality are opposed! The statistics are correct, but using them for forecasting turns out to be totally wrong.

The described situation illustrates the difference between ***statistical dependenc***e and ***causation***: statistics is applicable as long as those factors that influence the situation under study do not change, that is, directly or indirectly cause the observed effects. Observing the light in the absence of an intruder in the basement is not a reliable way to predict the situation in the presence of such an intrusion.

This simple example also demonstrates the obvious but systematically ignored fact that the main problem is not the difficulty of testing for a causal relationship but the lack of information about the factors that determine the statistical results of observations and allow building explicitly formulated causal relationships.

What happens if there are factors that are not recorded when studying the situation (building a model)? Due to the situation's specifics, if these factors do not change during the collection of information, as in our example, the statistical model may be wholly inapplicable. Suppose the unobservable factor in the recording of the facts is different. In that case, the result will be a more or less expected probability model, ***depending nevertheless on the statistics of the unobservable factors***. A logically rigorous approach to such situations is to recognize the presence of unobservable factors and be ready to revise the model because its use for decision-making will change the statistics for unobservable factors (perhaps change quite radically, as is the case in our example). A probabilistic model ***depends on how it is used*** - while causal relationships reflect the ***properties of the environment*** and ***do not depend on who uses them and how***.

The above example may seem far from reality, but it is not. For example, a drug that is effective in the early stages of the disease but of little use in the next stage is being tested for its effectiveness in hospitals where there are no patients in the early stages of the disease; as a result, the drug is recognized as ineffective. Inclusion of the drug in household first-aid kits makes it quite helpful but excludes the possibility of testing in hospitals.

Ignoring the fact that the statistical model depends on its use is a path to severe errors. Finding a cause-and-effect relationship that unambiguously connects the effect with the causes makes it possible to avoid such errors.

The natural criterion for the presence of a correctly detected causal relationship is the ***high probability of the predicted consequence***, which in this case is determined not by the presence of unaccounted factors but by the ***inaccuracy of registering the factors*** taken into account. An ideal causal relationship is a Boolean function; statistical differences from the ideal are determined by the errors in the registration of factors.

PLURALITY OF CAUSES

As a rule, an event results from a ***combination of several factors***. Furthermore, each factor can, in turn, be a consequence of several others and so on. As a rule, we are not talking about a cause but a "set of causes". For example, for a light bulb to glow, it must be inserted into the socket, and the switch must be turned on. A Boolean variable encodes the presence of a factor-cause, and a Boolean function describes the causal dependence with Boolean arguments. In the light bulb example, the two causes are connected by the logical operation "and", but any logical operation is possible. For example, when two switches are installed on two sides of a corridor or staircase, and the light is turned on, when the boolean variables describing the positions of the switches are the same - as a result, switching any of the switches changes the status of the lighting to reverse.

CAUSAL CHAINS

A single Boolean function describes an elementary cause-and-effect model; complex models are described by a set of functions whose arguments are combinations of factors from a common set of them.

The corresponding "***cause tree***" can have an arbitrarily large size, and the capabilities of the intelligent system determine this size. However, the detection (construction) of elementary cause-and-effect dependencies can be performed separately, independently of each other (including parallel analysis processes).

Testing the hypothesis about the presence of a causal relationship is not very difficult, but this does not make the detection/construction of dependence simple. There are many observable factors in natural environments, and the search for those of them, the combination of which is the cause of the desired event, encounters difficulties typical of ***combinatorial problems***. Another problem is the presence of ***chains of causality***: finding a connection between factors and a consequence associated with some intermediate events can be extremely difficult. Finally, situations are possible when ***certain factors of the desired dependence are just not collected***.

The constructed causal model can be used to find out ***what a particular combination of factors will lead to***, as well as to solve the inverse problem: ***finding a combination of factors that provide the desired effect***. An important aspect is that the ***technology of such an analysis is known*** - it is the basis for designing various kinds of automatic systems.

In cases where a factor is described ***quantitatively*** rather than a Boolean variable (yes/no), it is reduced to a Boolean using ***relationships between quantitative values*** (*greater than/less than/equal to*). For example, the condition for the collision of two balls is the moment when the distance between them decreases to a value equal to the sum of the radii. The argument factors can be numbers, but the result is Boolean.

When it comes to causality, the essential aspect is that the causal factors precede the effect. A Boolean function describing causation does not explicitly reflect this circumstance - it is an implied requirement. Nevertheless, when discovering (constructing) a causal relationship based on some accumulated information, the condition of the precedence of causes to the effect must be considered explicitly. Data about the appearance and disappearance of factors and the onset of consequences must be ordered in time. This requirement is absent in traditional probabilistic models based on correlation analysis.

Causal relationships are ***not symmetrical*** in nature. In the corridor lighting example above, controlled by two switches, we can tell what each switch will cause; but if the light is known to have been switched on, it is impossible to infer which switch being turned on caused it.

NOT EVERY DEPENDENCY IS A CAUSAL ONE

Many necessary dependencies used to describe the environment are not causal. For example, a consequence of the law of conservation of energy is a dependence that relates the altitude of the position of a flying object and its speed, but this relationship is not causal. Altitude is not a consequence of speed; speed is not a consequence of altitude; none of the factors involved precedes the other. They form a ***pair of interrelated quantities***. The relationship differs from the cause-and-effect relationship primarily because ***there are no events***: the quantities change ***smoothly and simultaneously***. The construction of such dependence does not require data order in time.

In complex environment models used to develop solutions by an intelligent system, both types of dependencies are combined into a composite model that inherits the specifics of both.

SUMMATION

- *Building cause-and-effect models require specific methods for analyzing experimental data.*
- *Causes precede effects; data for building a model must be ordered in time.*
- *Causal relationships are not symmetrical.*
- *Boolean functions describe causal relationships.*
- *Not all dependencies are causal.*
- *The complexity of the search for cause-and-effect relationships is due to the combinatorial nature of the problem and the possible lack of observation data on the factors-causes.*