A bird's eye view of causal models

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This is to summarize the key points relative to causal modelling.

The debate on causation

The debate on causation is made difficult by the lack of scientific consensus on the meaning of both scientific explanations and causation. Let's start with physics. In a nutshell, physics as a scientific theory consists in finding general laws of nature and explain contingent facts through logical deduction. That is, physics explains by stating general laws and make deductions from general laws. For instance, the heat equation is a law of nature. If we want to model the diffusion of temperature in a piece of metal, we solve the heat equation with numerical methods.

Formalized by Carl Hempel and Paul Oppenheim, this principle is called Deductive-Nomological (DN) principle. Research in physics has two objectives: finding more general laws and finding new deductions that describe specific empirical contexts. This notion of scientific explanations works even if we reject reductionism, and we believe that science is hierarchical. At each level in the hierarchy, we have laws of nature and deduction of specific facts.

Explanation by generalization and deduction is not causal, at least with the following definition of causation that we adopt here: A variable X is said to have a causal effect on a variable Y if after a change of the value of X the value or the distribution of Y is changed while the reverse is not true. This, however, is not the only definition of causation. The critical point is that we can solve the debate whether physics is causal or not only if we have a clear notion of causation. In the absence of a clear definition of causation the debate is purely terminological.

In addition, when we study complex systems, we might study systems whose behavior has not been axiomatized, and perhaps cannot be axiomatized. There are also sciences, such as psychology, which cannot be formulated with the DN principle. In these sciences, it might be difficult separating explanation from causation. For example, we might say that emission of CO_2 causes the earth temperature to increase. Statements like this are causal statements. Does it mean that science is causal?

Basic science that studies laws of nature is not causal. Basic science explains by performing inference from general laws to specific systems. However, applied science might study causal systems. But causality is not a law of nature. Causal systems are artefacts or natural systems with an internal structure which is responsible for causation. Psychology raises additional problems because the concepts of psychology are difficult to define. We might state that frustration causes aggressivity. Statements like this one are causal statements but how do we define frustration?

Therefore, we can conclude that axiomatic science such as physics is not causal but tends to explain with generalization-deduction. However, specific systems might exhibit a causal behavior due to their internal structure. There are sciences whose objective is to study specific systems. These systems might be causal, and the relative sciences might be causal.

Correlation is not causation; So, what is causation?

Two variables X and Y are said to be correlated if they tend to move together. Correlation is an empirical phenomenological finding without any notion of intervention: X and Y are correlated if they tend to move together in the samples we know. Causation is also an empirical finding but with the added notion of intervention. Following our definition, we say that X has a causal effect on Y if we can intervene on X so that after changing the value of X the value or the distribution of Y is changed but not viceversa.

Intervention is not necessarily a human action. An automatic pilot system of a plane must have a causal subsystem that controls the rudder, the ailerons, the throttle and many other flight-control devices. Intervention can also be performed by nature: for example, the changing of seasons has many causal effects on plants and animals.

Saying that X has a causal effect on Y is not a statement on the intrinsic nature of X and Y. Science remains agnostic as regards ontology. It is often said that causal effects happen because there is a causal mechanism that produces the effects. However, a causal mechanism is simply a structure of causal subsystems. Causal systems are typically hierarchical, but the entire causal structure is purely phenomenological.

We embrace a "manipulability" notion of causation. Causation means that we can intervene on certain variables and produce changes in other variables. Ultimately this statement is a consequence of basic laws plus a description of the structure of systems. For example, we can say that emission of CO_2 creates a layer of CO_2 in the atmosphere that reduce irradiation and therefore make the temperature of the Earth increase. Causal explanations of this type could be ultimately formulated in terms of basic physical laws plus other information of the structure of the Earth.

From the point of view of ontology, correlation and causation have the same status. The Reichenbach Principle states that there is a precise link between correlation and causation: two variables X and Y are correlated if and only if X causes Y, or Y causes X, or both are caused by a third variable Z. The Reichenbach principle is used in modelling, but exceptions have been found.

Some articles seem to hint that causation is a deeper level of knowledge than correlation. This is true but not in the sense that causation offers a better insight into the ontology. Causation is based on the structure of the system that we study. This is why algorithms can discover causal structures from correlations.

For business applications of causal models, we have to take a pragmatic view of correlation and causation. We can refine our causal analysis, introduce more variables and eventually form a network of causal relationships that imply the original statement that X has a causal effect on Y. We can also explain some causal relationships from basic laws.

Causal systems and causal models

Causal systems are ubiquitous. Every system where a part of the system controls another part is a causal system. Causal systems might be operated by humans or by other systems or by nature itself.

In the last three decades scientists and philosophers have studied systems that are not based on well-established theories. These systems are described by a set of random variables whose probability distribution is known or, at least, it can be estimated. Knowing the probability distribution implies that we know correlations between variables. The research question is whether it is possible to delve deeper and to find causal relationships between variables. A few examples will clarify.

Perhaps the most typical examples come from the medical field. Consider a large population of individuals who experience different symptoms and exhibit medical tests. The problem is to formulate diagnoses, that is, to associate diseases to symptoms. Human medical doctors formulate diagnoses based on their experience, diagnostic rules, and causal reasoning. We want to use causal AI to formulate diagnoses automatically to support medical doctors. The empirical data is a set of correlations symptom/test-disease, but we want to arrive at a deeper understanding of the cause of disease.

Or consider a population of people with a specific disease who receive different treatments. We want to understand what treatments are the most effective. We have empirical correlations between treatments and disease, but we want to arrive at a deeper understanding of the relationship between treatment and disease.

Finally consider firms described by a number of variables. Management intervenes on some variables to improve results, either operational or financial results. For example, management might invest in R&D to innovate products and improve sales and profitability. We have historical data on correlations between changes of the descriptive variables. Correlations are not sufficient to suggest strategies of intervention. We want to understand the causal links between variables.

One might immediately object that causation is a more serious affair that manipulating correlations. One expects that the causal relationship between symptoms and disease depends on the structure and functioning of the human body plus the biochemical relationships between all the substances produced in the body. We could make the same considerations about relationships between treatment and disease and also between variables describing a firm.

As we discussed above, causation is hierarchical. In some cases, we can describe the behavior of the system in terms of basic physical laws. However, in most cases of practical interest this is impossible because computations would be too long or even theoretically impossible. Given the true complexities of causal relationships, what contributions we expect to obtain from causal models?

Causal models offer a highly valuable practical insight. There is no firm theory of diseases and of treatment and there is no firm theory of the inner working of a firm. The dynamics of some diseases are well known but in many cases the dynamics is uncertain. And the association treatment-disease is far from being deterministic. Same considerations for the behavior of a firm. In practice we have to work with simplified relationships at an aggregate level.

Therefore, we assume that discovering causal relationships will unveil a practically useful level of causality. The depth of knowledge depends on the variables that we are using. Adding variables, we can reach a more detailed level of causality.

Discovering causal models

Methodologies and algorithms that discover causal relationships of models such as SCMs are based on making specific hypotheses on the probability distribution of variables that allow to determine the structure of conditional independence. The structure of conditional independence breaks down the global causal relationships into separate independent mechanisms. If we accept the hierarchical nature of causality, causal mechanisms in turn can be resolved into a structure of sub-mechanism.

Ultimately, the structure of causal mechanisms discovered by algorithms such as TETRAD should be coherent with more refined causal relationships implied by chemical or biological relationships or by the inner working of a firm's process. However, we cannot expect to discover complex chemical laws or behavioral patterns studying correlations between aggregated variables.

Practical and theoretical contributions

From the above considerations it should be clear that the causal relationships discovered by algorithms such as TETRAD are not necessarily good representations of a causal structure if the choice of variables is not adequate.

Therefore, the first practical research contribution is defining methodologies to help finding the optimal descriptive framework. In the case of firms, we should leverage the experience of managers. Somehow the causal model should be in agreement with management experience. If there are disagreements one should try understanding why the discovery process does not correspond to intuition. Causal models might offer a guide to change intuition of business processes.

Second, it should be understood that causal models are discovered and should live within a larger non causal model. This is obvious for technological models. A car braking system is a causal system that live inside a bigger system which is only partially causal. Some theoretical effort is needed to understand how a causal model might interact with a global model, for instance a VAR model in economics.

Third, causal models must evolve. We have established the point that the evolution of causal models is akin to paradigm changes in physics. In fact, evolution of causal models involves both the discovery of new structural equations and of new descriptive frameworks. Embedding causal models into an evolutionary framework is probably a big theoretical effort.

In summary, causal models can be helpful but they must be in agreement with the entire body of knowledge about the system they represent. The assumption of the hierarchical nature of causal systems is critical. Causal systems must e embedded in a general non-causal model and must evolve.