Why causal models? What are the advantages of causal modelling?

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In a nutshell, the answer is: because we want to control our environment. In social studies, in economics, in business, causal models are very useful to help make optimal decisions. In fact, economies as well as business or social systems are generally described by simplified global probabilistic models. Causal models are a recent scientific advance specifically designed to improve our ability to make optimal decisions.

There are other reasons for the recent interest in causal models related to Machine Learning and to Artificial Intelligence. Causal models might make machine learning more robust. However, here we are primarily concerned with business, economic, and social applications of causal modelling.

In technological applications the need for causal systems is obvious. Most artefacts are designed to be controlled. Causal models are embedded in the overall design of the systems. The engineers who design a plane are perfectly aware that the plane will be controlled by a pilot or even by an automatic pilot. The design of a plane will include sub-systems for piloting the plane. Most artefacts from cars to power stations, from home appliances to irrigation systems, need to be controlled and therefore include causal systems.

In technological applications controls are designed using all available scientific knowledge. Causality is part of the design of the system. In a number of cases designing control systems has become a science in itself. Automatic control systems are a well-developed area of engineering. How to make the interaction of human operators with machines safe and effective is also a well-developed area of engineering.

However, there are many human artefacts as well as natural systems whose behavior is not described by basic physical laws. These systems include economies, financial markets, firms, social systems, biological system. It is practically impossible, and probably even theoretically impossible, to describe the behavior of these systems in terms of basic physical laws. In fact, these systems are complex evolving systems. Complex systems are formed by many interacting parts. Complex systems exhibit emerging properties that cannot be explained in terms of basic laws.

The state of a system is described by a number of variables. Variables might be aggregates or abstract variables. For example, given a financial market stock market capitalization is an aggregate variable while volatility is an abstract variable. Consider a system and the descriptive variables. For example, consider a firm described by a set of N variables Xi, i=1,...,N. Variables might include sales, cost, investment in R&D and so on.

To optimize operations management might want to understand the relative behavior of changes of these variables. For instance, management might want to understand the relationship between sales and increments of the sales force. To this end, the classical tool is correlation and covariance analysis. Therefore, based on historical data, we can compute the correlation or covariance matrix.

But correlations are insufficient for good decision making. As explained in *A bird's eye view of causal systems* in this site, two variables X and Y are correlated if X causes Y, or Y causes X, or there is a third variable Z that causes both. If Y causes X or if Z causes both, changing X will have no effect on business operations. This is why correlations are insufficient for decision making.

Management wants to understand what variables needs to be changed to obtain the desired results. For example, management needs to determine the optimal changes of the sales force to achieve desired sales. Correlations are insufficient to this end. Management needs to understand the causal effects of changing the magnitude of the sales force and needs to understand if other changes are ultimately responsible for sales. It might be that product innovation is the real problem, or the cost of manufacturing.

To obtain these data one needs causal models. In the last three decades, scientists and philosophers have studied causal models and have invented algorithms for discovering causal models from covariance data plus a number of assumptions on data and on the characteristics of the systems. State of the art causal models such as the SCM are described in another entry in this site. Given the covariance matrix, causal algorithms can determine the causal structure of the variables and the strength of the causation links.

The choice of variables is critical. We need to add all variables that are truly involved in a firm's operations. For instance, to study the effects of product innovation we need variables that describe the qualitative aspects of the firm's products.

Firms and most systems of interest are dynamic systems whose variables change in time. Dynamic models of variables descriptive of firms or economies are often available. For instance, Vector AuroRegressive – VAR – models are often used. Given dynamic models we can compute the evolution of covariance matrices at different moments. The causal structure of the firm will evolve.

One observation is in order. It might happen that the descriptive framework of a firm, or of a system in general changes with time. As there are paradigm shifts in science, there are paradigm shifts in modelling. Management should be prepared to change the descriptive framework of a firm in response to its evolution.

Causal models are very useful decision support tools. They quantify causal relationships and therefore add quantitative support to decisions. The dynamic aspects of causality is a subject for research.