A few simple applications of causal modelling

In this paper I describe a few simple applications of causal modelling. These applications are simple to implement but useful. They only require the knowledge of the principles of causal modelling and access to a causal structure discovery software.

Before we describe these applications let's first recall the principle of causal modelling and discuss why they are useful. I will use the free software TETRAD to illustrate the various points. Causal models are mathematical models that describe causal structures. The best-known model is the Structural Equation Model – SEM – or the Structural Causal Model – SCM. Both models have the same form but, in general, SEM is deterministic while SCM is stochastic. Let's focus on SCM. I will state the relevant points of SCMs from the point of view of a user.

Suppose a system is described by a set of n variables $Xi, n = 1, \ldots, n$. A SCM is a set of structural equations:

$$Xi \coloneqq fi(PAi, ei)$$

Where the *fi* are deterministic functions, *PAi* is called the set of parents of *Xi* formed by all variables that have a causal effect on *Xi* and *ei* is a random disturbance. The above equation is not a usual functional equation but it is a structural equation that states that *Xi* is a function of the variables in *PAi* and *ei* but it is not invertible. It is an asymmetric relationship. The *ei* are supposed to be mutually independent.

The notion of causal effect is generally formulated in terms of *interventions*. Given two variables *X* and *Y*, *X* is said to have a causal effect on *Y*, if after an arbitrary change of *X* it is found that *Y* has also changed. In other words, by changing input *X* we can control output *Y*.

Given the structural equations and the assumption that the *ei* are independent variables, the joint distribution of the *Xi* is known. Suppose that the *Xi* are the nodes of a graph and that the structural equations define the links. Assume that the graph describing the system is a DAG that is a Directed Acyclic Graph where there no cycles. With additional assumptions, that essentially imply that the system is a causal system faithfully described by the above structural equations, then the joint probability distributions of the *Xi* can be factorized as:

$$p(Xi) = \prod p(Xi/PAi\,, ei)$$

This factorization in conditional probabilities represents the causal structure.

How do we proceed in practice? Software for causal discovery receives in input a covariance matrix and determine the structural equations and the causal graph from the covariance matrix. If one had the possibility of making experiments, then one could observe and measure the causal effects of different decisions. However, in many practical situations it is impossible to make experiments to determine the relative effects of different decisions. Causal models are very useful in these situations.

How do they work? There are different strategies. All strategies start with the assumption that there is a causal structure. Given this basic assumption, the most intuitive strategy is to search for the above conditional probability factorization. This is a difficult statistical task that can be performed with a series of conditional independence tests.

With the present level of discovery algorithms, users do not need to program any test. Software such as the PC algorithm performs all the necessary steps. Users compute the covariance matrix, a straightforward task, and the discovery algorithm does the work. Eventually expert inputs can be useful.

As we will illustrate in many business applications it would be very useful to understand causal relationships between variables. Knowledge of causal links would give us the ability to perform changes of input variables to obtain the desired results. In general, it is easy to determine correlations between different variables. However, correlations do not necessarily imply mutual causation. Correlations might be due to exogenous variables or to the joint effect of the variables we are considering. Algorithms for causal discovery tend to answer these questions.

Let’s now describe a few applications where this strategy is useful.

Sales

Sales managers have several objectives. They might desire to increase the loyalty of clients, reducing clients’ turnover. O simply they would like to increase sales within the constraints of their budgets and the products available for sales. But how? Adding salespersons? Giving more training of the sales force? More advertising? Adding sales channels? Targeting different prospective clients? A different message positioning their products?

Anyone who has been involved in sales probably has the memory of heated meetings on how to improve sales, of sessions of brainstorming in remote resorts trying to understand what to do. Because understanding the reaction of clients is not easy.

Sales managers and salespersons have their own experience and intuition but translating intuition into actions is not easy. One would like the support of data. There are books and reports on sales techniques and sales patterns. Firms have data on past sales, and eventually data on past market research. But all these data remain at the level of correlations. Here is where causal models might be very useful. Estimating a causal model give managers objective data on the relationships between variables involved in sales.

Of course we need the right type of data, the right type of variables. However, creating the right data is a problem that is not specific to causal models. Managers need to understand the effect of what they do even if they do not use formal causal models. Does advertising really promote sales or simply changes the market perception of a firm? One can cite endless cases where money spent on promotional activities or other marketing activities had undesired consequences. And the choice and training of the salesforce might give negative results.

Therefore, the use of causal models will force managers to do some serious thinking on the operations of their firms. This is nothing specific to causal models, but the discipline of causality might be the right occasion for a rigorous evaluation.

Directing a large salesforce

Many firms, even relatively small firms, use a large sales force of hundreds of independent sales agents or independent points of sales. Sale agents and points of sale work independently, often for several firms, in a given region. By using sales agents, firms do not have the fixed cost of their own sales. In addition, in most cases, firms sell products with a relatively low monetary value. By cumulating sales of different firms, agents can achieve their individual income goals. Still managing a large sales force is a challenging task. In general, there are large differences in sales performance of different agents. Firms need to know the cause of these differences. Of course, different regions have different sales potential but in addition the skills and abilities of agents might substantially differ.

Causal models are a very useful tool for helping firms to manage a sales force. A causal model of sales takes historical data from many different regions and construct a causal model of sales operations. A causal model is not simply a predictive model to assign a sales budget. A causal model tries to understand the reasons of the performance of different agents in different regions. These models would be particularly useful for launching new products and new services.

Investment management

Investment management is a complex activity typically based on forecasting returns. By forecasting returns investors can construct optimal portfolios and optimal asset allocation. Consider stock portfolios. Most forecasting models are based on correlations. Many models are non-linear models. For example, regime switching models are inherently non-linear models.

It would be very useful to understand causal relationships between financial and economic variables. This is a major project especially because many variables currently used are ill defined. For example, inflation is an ill-defined term for economies that are evolving complex systems. Products and services change qualitatively and are subject to a process of innovation where old products are continuously replaced by new products and the global spectrum of products keeps on increasing. Given these situations the deployment of causal models is a holistic process with possible paradigm shifts.

Still investment managers might find it useful to begin understanding the causal nature of the investment process. Given the abundance of data, investment managers could begin to model causal relationships between fundamental quantities such as indexes and some macroeconomic quantities.

Economics and also finance theory need a major overhaul because the basic structure of economic and financial variables is not capable to represent qualitative changes. This is a major conceptual problem in a world which is facing sustainability issues. In the future much growth should come from qualitative changes. However, it is unlikely that major theoretical changes will happen soon. Still causality will play a role in future modelling and therefore it would be useful that investors begin to outline the formal causal structure of markets.