An Introduction to Bayesian Networks

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Uncertainty and Artificial Intelligence

Artificial Intelligence can be defined as the science of automating human mental processes. Of course, a machine executing a human task only makes sense if the process can be better, cheaper and/or faster executed by the machine than by a human being.
The benefits are obvious if the process has at least one of the following features:

- Memorizing and computing abilities are essential for its execution (1).
- Cultural, educational or emotional factors, stress and fatigue tend to perturb or alter its execution by human beings (2).

Let us consider a dramatic example of a human process failure, the Challenger disaster, on January 28, 1986. The accident was caused by a leak through a faulty seal in one of the solid rocket boosters. The day was unusually cold (minus 2°C, approximately 10°C below the average temperature at this time of the year), and the joints did not work properly. It has been argued that the disaster would not have happened if the possibility of such a low temperature had been considered, and also, that the design failure was due to the commonplace 'winters in Florida are mild'. One has to be extremely careful with assertions regarding the causes of such a disaster. Let us assume however, for the purpose of the analysis, that the cold temperature was indeed the initiating event of the accident. Then the design failure and its dramatic consequences can either be attributed to a limitation of human capabilities: considering all possible values of each parameter directly or indirectly affecting the launch of the shuttle was impossible (1), or alternatively, be interpreted as the consequence of a cultural bias: the idea that 'winters in Florida are mild' (2).

The limitations of human mental capacities (1) are more noticeable and tend to have more serious consequences, in a context of uncertainty. Consider, an investment decision regarding, for example, a power plant. Many parameters (fuel costs, performance and availability of the plant, electricity prices) - and their evolutions over several decades - need to be taken into account to evaluate the rate of return of the investment: traditional deterministic evaluations are quite complex; considering a probability distribution for each of the relevant parameters make them untractable.
Similarly, psychological effects (2) play a greater role in a context of uncertainty. Randomness always generates stress. The reason why traffic jams, outages in trains, delays in flights make people so nervous is not the loss of time *per se*, but the uncertainty regarding how much time is going to be lost. Depending on the individuals, randomness can be destabilizing, ' paralysing ' or on the contrary, exciting or even exhilarating. These effects confuse human rationality.
Our analysis thus suggests that the potential contribution of Artificial Intelligence is greater in a context of uncertainty. This is obvious in the field of board games, which has been used as a benchmark to the AI methods since the infancy of this science. Nowadays, machines perform better than the best human experts in many games. This superiority, however, was achieved much earlier in the games involving randomness than in games in which the sequence of events only results from the decisions of the players. In 1979, world backgammon champion Luigi Villa was defeated in a 7-point match by a program called BKG 9.8. It was not before eighteen years later - a very long time if you consider the tremendous improvements of the machines capacities[1] - before a chess program *Deep Blue* could beat the best player of the world Garry Kasparov, in a 6-game match.

Bayesian Networks

CONCEPTUALS TOOLS to model and quantify uncertainty are available since the development of probability theory by Blaise Pascal, in the 17th century. However, combinatorial explosion effects tend to blunt their practical implementation. If the rentability of an investment depends on ten uncertain parameters, and if each of them takes on ten different values, then one has to identify, analyse and affect probabilities to ten billions (10^{10}) scenarios to find the best decision. Such an approach is unlikely to lead to a convincing and robust decision support.
Bayesian Networks, developed in the 1990s, are relatively intuitive models which help to reduce the intrinsic complexity of probabilistic approaches. Given uncertain and mutually influenced variables, the key idea is to focus on direct and significant influences between them, and to represent the influences in a diagram of boxes and arrows.

[1] To illustrate the improvements in computing performances in the period: in 1979, 1 million correct decimal digits of the number π (3.14159265...) had been computed; eighteen years later: 51 billions!

Figure 1 is an example of Bayesian network used as a decision support. The model evaluates the consequences, for a ski resort, of investing in a snow cannon. Two output variables are considered: financial result and customer satisfaction. The snow cannon variable is a decision variable. Its value depends only on the will of the ski resort managers. Weather variables such as 'Snowfall' and 'Sunshine' are not influenced by any other variable in the model. The seven other variables depend, more or less, on the invest decision and on the climatic parameters. These dependencies are described in 'conditional probability tables'. Decision aiding indicators (e.g., the expected financial results with and without the snow cannon) can be produced on the basis of the probability distributions of the two output variables. The model may also be used to simulate scenarios, e.g., a scenario of lack of snow.

Suppose that we choose to consider ten possible values (or range of values) for each variable. Then, the model is defined by approximately 3,000 probabilities, whereas ten billions configurations of the variables are theoretically possible. Apart from this dramatic reduction of the initial complexity of the problem, the user-friendly, graphical representation of the model facilitates the discussions between experts and decision-makers, which can easily be involved in the model construction.

Figure 1: Example of Bayesian network: the consequences of a decision (managers of a ski resort buying a snow cannon) on the financial result and the customer satisfaction.