Confidence-based Representation in Decision Making

Roberto Rossi*
roberto.rossi@ed.ac.uk
Business School
University of Edinburgh
Edinburgh, UK

February 7, 2017

Abstraction (derived from Latin abstrahere “to strip off, remove forcibly”) is “the process which allows people to consider what is relevant and to forget a lot of irrelevant details which would get in the way of what they are trying to do” [Giunchiglia and Walsh, 1992]. Abstraction-based processes are pervasive in human reasoning. The earliest and most common use of abstraction was in problem solving. Abstraction maps a “ground” representation of the problem onto a new “abstract” representation, which preserves certain desirable properties and is simpler to handle, since it is built by “throwing away details” of the ground representation [Holte and Choueiry, 2003].

Management science is concerned with modelling and solving managerial decision problems. Problems investigated in the literature are generally abstracted from real world cases. This process of abstraction is necessarily non-deductive: it is led by inductive and/or abductive reasoning and cannot represent nor preserve all (potentially infinite) properties of the real problem faced by a manager [Popper, 1934]. Unfortunately, non-deductive reasoning is often representation dependent: representing the same situation in two different ways may lead to different answers. For instance, Ptolemy’s epicyclic solar system was more accurate predicting the positions of planets than Copernicus’ view, until Kepler introduced the possibility that orbits are ellipses. Interestingly, the authors in Halpern and Koller [2004] remark that representation independence is too much to expect if one aims for nontrivial conclusions and that researchers in machine learning and statistics have long realised that representation bias is an inevitable component of effective inductive reasoning.

A management science model, like any other scientific model, is essentially a *hypothesis*. This perspective finds its origins in the scientific method pioneered by Galileo and Bacon and reinforced by Karl Popper’s explication of the hypothetico-deductive model [Popper, 1963] in which the hypothesis is considered to be just “a guess.” As such, one may say that there is no single “correct” or “true” model. There are instead models that reflect, to a greater or lesser extent, certain aspects of reality that are of interest to the decision maker.

This perspective on the nature of decision support models is often lost in management science, because researchers tend to mainly focus on the analytical part of the scientific method, heavily influenced by the strong tradition of Platonic realism found in mathematics [Tait, 1986], while disregarding the importance of the inductive and/or abductive aspects of modelling. In short, classical management science models focus on providing a single optimal or near-optimal solution, obtained analytically, to an abstracted problem.

*29 Buccleuch place, EH8 9JS, Edinburgh, UK

This mechanistic view of decision support, in which to a set of input parameters corresponds a single optimal choice, instead of generating *creative engagement* and leaving scope for *interrogation*, *mediation* and *deliberation*, simply narrows down decision maker options to a single one. In reality, decision maker judgment is a subjective matter in which bias introduced by intentions can be significant [Tawfik, 2004, Tversky and Kahneman, 1974]. This is especially true when it comes to estimation and assessment of probabilities [Nau, 2001, Sandbu, 2017]. As remarked in Einhorn and Hogarth [1981], "the conditional nature of optimal models has not been appreciated and too few researchers have considered their limitations [...] To consider human judgment as suboptimal without discussion of the limitations of optimal models is naive." Furthermore, "the imposition of (subjective) values for resolving conflicts leads to rejecting *objective* optimality and replacing it with the criterion of consistency with one's goals and values."

The normative nature of mainstream management science models clashes with the subjective nature of decision making under uncertainty; most management science models do not satisfactorily address the problem of reconciling conflicting views and supporting deliberation in the process of reaching a closure.

In an attempt to begin addressing the above problem, in Rossi et al. [2014] we introduced "Confidence-based Reasoning" (CBR). CBR is a novel multidisciplinary approach that brings together statistics, operations research and computer science to support managerial decisions. This approach uses past (subjective) data to prune decisions that are inconsistent with one's goals and/or constraints at prescribed confidence level. For each remaining decision it provides a confidence interval for the associated payoff. CBR has several analogies with established techniques in statistics. When a survey is conducted on a sample population — e.g. an electoral poll — a statistician typically associates a confidence level with the results obtained from the chosen sample population. For instance, one may claim that with 90% confidence the mean being estimated is within a given interval. In Rossi et al. [2015] we argue that the very same approach may be adopted in decision making under uncertainty. More specifically, we suggest that a decision maker, instead of looking for a single exact or approximate decision, may instead aim to "estimate" whether a decision is feasible or optimal according to a given confidence level α and a tolerated estimation error $\pm\vartheta$. By choosing given values for α and ϑ the set of candidate solutions, i.e. feasible or optimal decisions, may vary. For this reason, we introduced a new notion of solution that is parameterised by these two parameters and that we name (α, ϑ)-solution [Rossi et al., 2011]. One should note that an approach of this kind to decision making under uncertainty has been recently advocated by Costantini [2011]. Most importantly, our approach does not lead to a single optimal or near-optimal solution, but to a set of "candidate" optimal solutions. Similarly to statements made in the context of statistical inference, rejection or inclusion of solutions in the candidate set is, by its very nature, *provisional*. This means it can be revised when new or updated subjective evidence is taken into account. In turn, this leaves scope for interrogation, mediation and deliberation among decision makers. In brief, a CBR model is not a truth-generating machine. It is a tool that can be used to disregard decisions that, based on available subjective evidence, a decision maker provisionally considers suboptimal or infeasible according to the chosen confidence level and error tolerance threshold.

Judged rationality seeks a trade-off between the efficiency of means to ends and the "goodness" of the goal [Einhorn and Hogarth, 1981]. The former has been historically investigated by decision scientists, the latter by moral philosophers and theologians. However, in practice these two aspects are deeply intertwined in the decision making process, since the effectiveness of decision support may come from structuring tasks so that the nature of one's goal is clarified. We believe that the development of decision support tools that leave scope for deliberation, such as CBR, plays a pivotal role in bridging these two worlds.

References

Domenico Costantini. *Verso una rappresentazione probabilistica del mondo*. Emmebi Edizioni Firenze, January 2011.

H. J. Einhorn and R. M. Hogarth. Behavioral decision theory: Processes of judgement and choice. *Annual Review of Psychology*, 32(1):53–88, 1981.

Fausto Giunchiglia and Toby Walsh. A theory of abstraction. *Artificial Intelligence*, 57(2-3): 323–389, October 1992. ISSN 0004-3702.

Joseph Y. Halpern and Daphne Koller. Representation dependence in probabilistic inference. *Journal of Artificial Intelligence Research (JAIR)*, 21:319–356, 2004.

Robert C. Holte and Berthe Y. Choueiry. Abstraction and reformulation in artificial intelligence. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 358(1435):1197–1204, July 2003. ISSN 1471-2970.

Robert F. Nau. De finetti was right: Probability does not exist. *Theory and Decision*, 51(2-4): 89–124, 2001.

Karl Popper. *The Logic of Scientific Discovery (Routledge Classics)*. Routledge classics. Routledge, 2 edition, March 1934.

Karl Popper. *Conjectures and Refutations: The Growth of Scientific Knowledge (Routledge Classics)*. Routledge, 2nd edition, August 1963.

R. Rossi, B. Hnich, S. A. Tarim, and S. Prestwich. Finding (α,ϑ)-solutions via sampled SCSP. In T. Walsh, editor, *Proceedings of the 22nd International Joint Conference on Artificial Intelligence, IJCAI 2011, Barcelona, Spain, July 16-22*, pages 2172–2177. AAAI Press, July 2011.

Roberto Rossi, Steven Prestwich, S. Armagan Tarim, and Brahim Hnich. Confidence-based optimisation for the newsvendor problem under binomial, poisson and exponential demand. *European Journal of Operational Research*, 239(3):674–684, December 2014.

Roberto Rossi, Brahim Hnich, S. Armagan Tarim, and Steven Prestwich. Confidence-based reasoning in stochastic constraint programming. *Artificial Intelligence*, 228:129–152, November 2015.

Martin Sandbu. Economic forecasters need alternative thinking in this uncertain world. *Financial Times (online)*, January 2017. URL `http://www.ft.com/content/985b47f6-e6db-11e6-893c-082c54a7f539`.

William W. Tait. Truth and proof: The platonism of mathematics. *Synthese*, 69(3):341–370, 1986.

Ahmed Y Tawfik. Inductive reasoning and chance discovery. *Minds and Machines*, 14(4):441–451, 2004.

Amos Tversky and Daniel Kahneman. Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131, 1974.