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HYBRID PROBABILISTIC SYSTEMS

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1. Introduction

This special issue collects revised and extended versions of papers presented at the Special Track on Uncertain Reasoning held at the 12th International FLAIRS Conference[1]. These papers represent an interesting trend in papers submitted to the Special Track as well as reasoning under uncertainty in general. This is the trend towards combining probability with elements of other techniques from artificial intelligence, such as classical and non-classical logics, genetic algorithms, and machine learning.

The Special Track on Uncertain Reasoning has been held at FLAIRS annually since 1996[2,3,4]. It was founded by Eric Neufeld, and for the first four years was chaired by him in conjunction with Ahmed Tawfik and, later, Simon Parsons. The aim of the Special Track is specific—to provide a forum for the presentation and discussion of new ideas about reasoning under uncertainty, especially those that are eclectic, in the sense of drawing on a number of different approaches from the uncertainty canon, and innovative, in the sense of breaking new ground rather than being tweaks on existing ideas. This is a rather bold aim has been achieved, and the track has witnessed a good number of high quality original papers[5].

2. Hybrid probabilistic reasoning

The story of probabilistic reasoning in artificial intelligence is a convoluted one. When researchers in artificial intelligence first realised that representing and reasoning with uncertainty was an important, indeed necessary, task probability was, in many ways, an obvious choice as a basis for doing this. The theory had been around in one form or other since the time of Laplace (his "Philosophical Essay on Probabilities" dates from 1795), and, as a result, there was a huge literature on probability and statistics. However, probability did not fit neatly with the prevailing orthodoxy in artificial intelligence at the time, which was to use first order logic or production rules as the basis of any knowledge representation, despite some attempts to bridge this gap[6,7]. In addition, many people had reservations about the amount of data which was required in order to build probabilistic models, and the subsequent computational expense of updating these during inference, which could only be resolved with unrealistic independence assumptions. The result was a side-lining of work on probabilistic reasoning from the mainstream of artificial intelligence research.

The effect of this side-lining was threefold. First, there was a general move away from work on uncertainty, or at least numerical approaches to dealing with it, in favour of techniques such as nonmonotonic reasoning, for which the "golden age" coincides closely with the era of probability theory's relative unrespectability (despite the success of probability as a way of accounting for defeasible reasoning in general[8]). Second, many people who were still convinced that uncertainty was an important topic turned to the use of alternate numerical calculi such as fuzzy sets[9], Dempster-Shafer theory[10], or certainty factors[11]. The third effect was to make those people who still believed that probability was a viable technique, if not the *only* technique for handling uncertainty, redouble their efforts to show that it could be useful[12].

The eventual outcome of this latter strand of work, albeit after some years toiling in obscurity, was the field of Bayesian Networks[13,14]. Bayesian networks not only revolutionised the area of reasoning under uncertainty, but played a major role in the rise of probability theory to respectability within mainstream artificial intelligence. The final proof of this new respectability for those still sceptical might well be the Award for Research Excellence presented to Judea Pearl, the architect of Bayesian networks, at the 1999 *International Joint Conference on Artificial Intelligence* (the most important event in the artificial intelligence calendar). Possibly even more telling is the growth in papers on the subject and the number of invited talks given by people from the Bayesian networks community to mainstream artificial intelligence events.

Bayesian networks, of course, provide an alternative metaphor for knowledge representation and reasoning from that provided by logic, and for many years it was work on getting this right—finding ways to represent new types of information and mechanisms for improving the speed of inference—that dominated work in the field. However, this is no longer the case. As researchers become content that the underlying representational and computational machinery is effective, they are looking at wider issues. One such issue is that of using machine learning techniques to help construct the networks, thus bypassing the knowledge acquisition bottleneck of determining all the relevant conditional independencies that need to be known to build a network. Another issue is that of applying probability, in a broad sense, to problems in areas of artificial intelligence outside of the traditional remit of reasoning under uncertainty, and of applying techniques from those other areas in probabilistic reasoning. It is this hybridisation between probability and other areas of artificial intelligence which is the subject of this issue and which leads us to use the term "Hybrid probabilistic reasoning".

3. The papers

This issue contains five papers:

- Non-determinism and uncertainty in the situation calculus, J. Pinto, A. Sernadas, C. Sernadas, and P. Mateus;
- A factorized representation of independence of causal influence and lazy propagation, A. L. Madsen and B. D'Ambrosio;
- Directing genetic algorithms for probabilistic reasoning through reinforcement learning, X. Zhong and E. Santos Jr;
- Committees of learning agents, L. Asker, M. Danielson, and L. Ekenberg; and
- On proofs in System P, S. Parsons and R. A. Bourne.

All are examples of hybrid probabilistic reasoning, though the degree of hybridisation varies. Pinto *et al.* illustrate what we call *strong hybridisation*. The paper takes the situation calculus[15], a classic work of artificial intelligence and the first attempt to solve the frame problem, and adds ideas from probability theory to extend the representational range of the formalism. We call this "strong hybridisation" because of this big gain in representational power. Without the use of probability (or some other uncertainty formalism), the situation calculus would be unable to capture the kind of statistical events that Pinto *et al.*'s formalism can deal with. Similar strong hybridisation is discussed in the paper by Parsons and Bourne. Their work is based on System P[16], a logical approach to default reasoning that was given a probabilistic interpretation by Pearl[13] and Adams[17]. In this case the hybridisation consists of making the probabilities associated with the default conclusions explicit, thus combining the default reasoning mechanism of System P with a mechanism for establishing exactly how likely conclusions are to hold.

In contrast to these papers on strong hybridisation, the remaining papers are what we term *weak hybridisation*.* We distinguish weak hybridisation by the fact

*There is no derogatory intent in these names. The terms "strong" and "weak" merely refer to the degree of hybridisation, and there is no suggestion that strong hybridisation is somehow better than weak hybridisation.

that the hybridisation does not make it possible to do new things, but allows those things which can already be done to be done faster, or better, than before. For example, the paper by Zhong and Santos deals with belief revision in Bayesian networks. This is a process which is well understood, and for which algorithms already exist (for example those given by Pearl[13]). However, the general problem is known to be NP-hard, and so Zhong and Santos have looked at the use of genetic algorithms to improve the efficiency of the belief revision process. In particular, their paper explores the use of reinforcement learning to classify Bayesian networks in order to guide the use of genetic algorithms to perform more efficient belief revision than is possible using genetic algorithms more naively.

Hybridisation between probabilistic techniques and machine learning techniques is also the concern of Asker *et al.*. Their paper investigates the use of decision theory to identify severe problems in power plant operation. Decisions are made on the basis of a set of classifiers, and the classifiers are trained using techniques from machine learning. Once again it would be possible to do this without the hybridisation since the classifiers could be constructed on the basis of expert opinion rather than on the basis of training data. However, the use of machine learning techniques makes it possible for the classifiers to evolve over time, providing a more robust solution. The final paper in the issue is that by Madsen and D'Ambrosio. This hybridises the use of lazy propagation[18] and factorized representation[19] to permit more efficient inference in Bayesian networks than is possible using either approach on its own.

These papers, then, tap some of the possibilities in the area of hybrid probabilistic reasoning. Future FLAIRS Special Tracks will doubtless see others.

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