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Some Useful Properties of Probabilistic Knowledge Representations From the Point of View of Intelligent Systems

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Abstract. Although probabilistic knowledge representations and probabilistic reasoning have by now secured their position in intelligent systems research, it is not uncommon to encounter misunderstanding of their foundations and lack of appreciation for their strengths. This paper discusses five issues related to intelligent systems research and shows how they are addressed by the probabilistic knowledge representations.
Directed probabilistic graphs capture essential qualitative properties of a domain, along with its causal structure. Concepts such as relevance and conflicting evidence have a natural, formally sound meaning in probabilistic models. Probabilistic schemes support sound reasoning at a variety of levels ranging from purely quantitative to purely qualitative levels. Probabilistic knowledge representations provide insight into the foundations of logic-based schemes for reasoning under uncertainty, showing their difficulties in highly uncertain domains. Finally, probabilistic knowledge representations support automatic generation of understandable explanations of inference for the sake of user interfaces to intelligent systems.

1 INTRODUCTION

Reasoning within such disciplines as engineering, science, management, or medicine is usually based on formal, mathematical methods employing probabilistic treatment of uncertainty. While heuristic methods and ad-hoc reasoning schemes may in many domains perform well, most engineers will be reluctant to rely on them whenever the cost of making an error is high. To give an extreme example, few people would choose to fly airplanes built using heuristic principles over airplanes built using the laws of aerodynamics. The attractiveness of probability theory lies in its soundness and its guarantees concerning long-term performance. Similarly to the first order logic in deterministic reasoning, probability theory can be viewed as a gold standard for rationality in reasoning under uncertainty. Following its axioms protects from some elementary inconsistencies. Their violation, on the other hand, can be demonstrated to lead to sure losses [19]. Application of probabilistic methods in intelligent systems makes these systems philosophically distinct from those based on the mainstream artificial intelligence methods. Rather than imitating humans, they support human reasoning by a normative theory of decision making. A useful analogy is that of an electronic calculator: the calculator aids people's limited capacity for mental arithmetics rather than imitating it. The distrust for human capabilities for reasoning under uncertainty has strong empirical support [17].

This paper discusses five issues related to intelligent systems research and shows how they are addressed by the probabilistic knowledge representations. It is a review paper and it accessibly and informally summarizes only the most important results. Pointers will be given to original papers for those readers who are interested in details and in a formal exposition. The remainder of this paper is structured as follows. Section 2 reviews the foundations of probabilistic knowledge representations. Section 3 is devoted to the issue of causality in models and shows the ease with which probabilistic models represent the causal structure of the underlying domain. Section 4 discusses the issue of relevance in probabilistic context. Section 5 shows that probability theory supports computationally efficient qualitative schemes for reasoning under uncertainty. Section 6 lays a link between probabilistic and logic-based schemes for reasoning under uncertainty, showing the difficulties that logic-based schemes face in highly uncertain domains. Finally, Section 7 discusses the issues of knowledge elicitation and explanation in the context of probabilistic systems.

2 FOUNDATIONS

As outlined carefully by Leonard Savage in his influential book on the foundations of Bayesian probability theory and decision theory [19], probabilistic reasoning is always confined to a well defined set of uncertain variables, which Savage refers to as "small world." A probabilistic model consists of an explicit specification of these variables and the information about the probability distribution over all possible combinations of their outcomes,[1] known as the joint probability distribution. It is a fundamental assumption of the Bayesian approach that the joint probability distribution exists and if needed can

[1] A combination of outcomes of all variables, i.e., an element of the Cartesian product of sets of outcomes of all individual model's variables, can be succinctly defined as a state. There is a richness of terms used to describe states of a model: extension, instantiation, possible world, scenario, etc. Throughout this paper, I will attempt to use the term *state of a model* or briefly *state* whenever possible.

be elicited from a human expert.[2] If there are n propositional variables in a model, there are 2^n states of the model and, effectively, the joint probability distribution consists of 2^n numbers. It is seldom the case that all these numbers have to be elicited and stored in a model. By factorizing the joint probability distribution and exploring the independences existing in the domain, once can reduce it to a product of a small number of probabilities. Such factorized form can be represented by a directed graph, such as a *Bayesian belief network* (BBN) [18]. Nodes in a BBN represent random variables. Lack of a directed arc between a node a and a node b means that variables a and b are independent conditional on some subset Ψ of other variables in the model (Ψ can also be empty).

Figure 1 shows an example of a BBN modeling various causes of low level of car engine oil. The interactions between variables in this model are uncertain in general. A

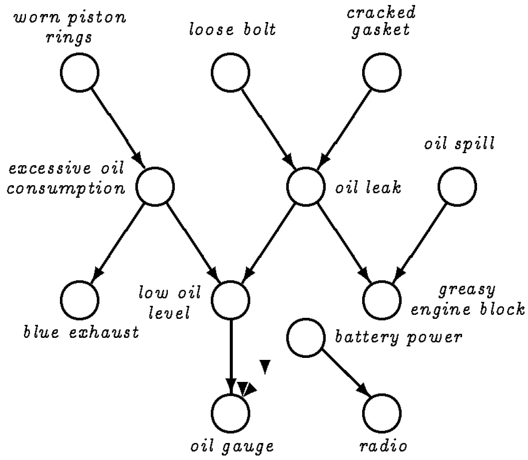

Fig. 1. An example of a Bayesian belief network

crack in the gasket may result in *oil leak*, but there may be an *oil leak* without a *crack in the gasket* or there may be a *crack in the gasket* that does not cause *oil leak*. There are many independences represented explicitly in this graph. And so, *loose bolt* and *crack in the gasket* are independent. They become dependent conditional on *oil leak* or any of its descendants. *Worn piston rings* is independent on *blue exhaust* conditional on *excessive oil consumption*. The graphical model, such as the one in Figure 1, is usually supplemented by its numerical properties, expressed by matrices of conditional probabilities stored in each of the nodes. With each of the 12 variables in this model being propositional, the complete joint probability distribution contains $2^{12} = 4096$ numbers. Explicit information

[2] It is not necessary, however, to specify it numerically in order to perform useful reasoning — in fact a specification of the constraints on this joint probability distribution and reasoning in terms of these constraints leads to schemes of less specificity and even purely qualitative schemes, as will be shown in Section 5.

about independences included in the model allows for specifying it by only 54 numbers. Both, the structure and the numerical probability distributions in a BBN are elicited from a human expert and are a reflection of the expert's subjective view of a real world system. Scientific knowledge about the system, both in terms of the structure and frequency data, if available, can be easily incorporated in the model. It is apparent from the above example that BBNs offer a compact representation of joint probability distributions and are capable of practical representation of large models. BBNs can be easily extended with decision and value variables for modeling decision problems. Such amended graphs are known as *influence diagrams* [20].

3 PROBABILITY, CAUSALITY, AND ACTION

It seems to be an accepted view in psychology that humans attempt to achieve a coherent interpretation of the events that they observe by organizing their knowledge in schemas consisting of cause-effect relations. This holds for both scientific and everyday reasoning. Scarcity of references to causality in most statistics textbooks and the disclaimers that usually surround the term "causation" create the impression that causality forms a negative and unnecessary ballast on human mind that cannot be reconciled with the probabilistic approach. In fact, causality and probability are closely related. While probabilistic relations indeed do not imply causality, the latter normally implies a pattern of probabilistic interdependencies and these, in turn, provide clues about causality. A generally accepted necessary condition for causality is statistical dependence. For a to be considered a cause of b in a context $\mathcal{S}$, it is necessary that $Pr(B|A\mathcal{S}) \neq Pr(B|\overline{A}\mathcal{S})$, i.e., the presence of a must have impact on the probability of b. Knowledge of the direction of causality allows humans to predict the effects of their actions.

It turns out that directed graphs readily combine the symmetric view of probabilistic dependence with the asymmetry of causality. A directed graph can be given causal interpretation and can be viewed as a structural model of the underlying domain. Simon and I [10] tied the work on structural equations models in econometric and AI to probabilistic models and formulated the semantic conditions under which a directed probabilistic graph is causal. We have shown that a node and all its direct predecessors in a graph play a role that is equivalent to that of a structural equation. Structural equations in econometric are equations describing unique mechanisms acting in the system [22]. For example, in a simple physical system such as a pendulum, one of the mechanisms might be described by the equation $f = mg$, where m is the mass of the pendulum, g is Earth's gravitational constant, and f the force with which Earth acts on the pendulum. Mechanisms are identifiable by underlying physical, chemical, social, or other laws, physical adjacency, connection, or interaction. As we have shown, one can view each node in a probabilistic graph along with its direct predecessors as a qualitative specification of a mechanism acting in a system.

There are two important reasons for interest in causality in the context of intelligent systems. The first is that models that include causal information are natural and in general easier to construct and modify [14, 21]. Such models are also easier for the system to explain and for their users to comprehend [3, 25]. The theoretical link between structural equations models and directed probabilistic graphs shows how prior theoretical knowledge about a domain, captured in structural equations, can aid construction of BBNs. If we happen to know the mechanism tying a group of variables, we know that these variables will be adjacent in the constructed graph. Existing theoretical knowledge, if incorporated at the model building stage, can aid human experts, make model building easier, and, finally, improve the quality of constructed models.

The second reason for interest in causality is that autonomous intelligent planning systems should be able to predict the effects of their actions. For this, the model that they base their reasoning on, i.e., their picture of the world, needs to be causal. Spirtes et al. [23] show in what they call the *manipulation theorem*, that it is straightforward to predict the effect of manipulating a variable in a probabilistic causal graph. The probability distribution over the manipulated graph can be obtained by modifying the conditional distributions of the manipulated variables. Imposing a value on a variable x through an external intervention, in particular, amounts to removing all arcs in the graph that point at x. Assuming that the model of Figure 1 is causal, using a theorem by Spirtes et al., we can easily predict the effect of external interventions to the model. And so, manipulation of the variable *greasy engine block* (for example, by washing the engine) will have no effect on any other variable in the model. On the other hand, manipulation of the variable *low oil level* (for example, by adding oil) will impact the indication of the *oil gauge*, but not variables *excessive oil consumption*, *oil leak*, or any of the other variables in the graph.

4 RELEVANCE

Typically, an intelligent system includes a large body of domain knowledge that is essential for its reasoning. An important problem that such a system faces is identifying those parts of the domain knowledge that are relevant for the query that it is addressing. "Small worlds" modeled by probabilistic systems may include hundreds or thousands of variables. Each of the variables of a probabilistic model may be relevant for some types of reasoning within this domain, but rarely will all of them participate in reasoning related to a single query. Too much information may unnecessarily degrade the system's performance. Focusing on the most relevant part of the model is also crucial in communicating its results: too many irrelevant facts will have a confounding effect on most users. It is important, therefore, to identify a subset of the "small world" including only those elements of the domain model that are directly relevant to a particular problem. Suermondt and I [11] recently summarized our work on the methods that can be used for such reduction in probabilistic models. Each of these methods is fairly well understood theoretically and practically implemented.

One possible way of reducing the size of the model is instantiating evidence variables to their observed values. The observed evidence may be causally sufficient to imply the values of other, as yet unobserved nodes (e.g., if a patient is male, it implies that he is not pregnant). Similarly, observed evidence may imply other nodes that are causally necessary for that evidence to occur (e.g., observing that the *radio* works might in our simple model imply *battery power*). Each instantiation reduces the number of uncertain variables and, hence, reduces the computational complexity of inference. Further, instantiations can lead to additional reductions, as they may screen off other variables by making them independent of the variables of interest.

Parts of the model that are probabilistically independent from a node of interest t given the observed evidence are clearly not relevant to reasoning about t. Geiger et al. [12] show a computationally efficient way of identifying nodes that are probabilistically independent from a set of nodes of interest given a set of observations by exploring independences implied by the structural properties of the graph. They base their algorithm on a condition known as d-separation, binding probabilistic independence to the structure of the graph. Reduction achieved by means of d-separation can be significant. For example, observing *excessive oil consumption*, makes each of the variables in the example graph independent of *worn piston rings*. If this is the variable of interest, almost the whole graph can be reduced.

Further reduction of the graph can be performed by removing nodes that are not computationally relevant to the nodes of interest given the evidence, known as *barren nodes* [20]. Barren nodes are uninstantiated child-less nodes in the graph. They depend on the evidence, but do not contribute to the change in probability of the target node and are, therefore, computationally irrelevant. If the presence of *low oil level* is unknown, then the probability distribution of *low oil level* is not necessary for computing the belief in *blue exhaust*, *excessive oil consumption*, *oil leak*, and ancestors of the latter two.

A probabilistic graph is not always capable of representing independences explicitly [18]. The d-separation criterion assumes, for example, that an instantiated head-to-head node makes its predecessors probabilistically dependent. This is not the case, for example, for a common type of interaction known as Noisy–OR gate, when the common effect has been observed to be absent [9]. A careful study of the probability distribution matrices in a graph may reveal similar circumstances and further opportunities for reduction. Procedures for this examination follow straightforwardly from the probabilistic definition of independence.

For some applications, such as user interfaces, there is another class of variables that can be reduced. This class consists of those predecessor nodes that do not take active part in propagation of belief from the evidence to the target. Both Suermondt's [24] and my work with Henrion [8] use the concept of chains of reasoning, which are the union of all active trails from the evidence to the target variable. Suermondt calls the irrelevant antecedent nodes *nuisance nodes*. A nuisance node, given evidence e and variable of interest t, is a node that is computationally related to t given e but is not part of any active trail from e to t. If we are interested in the relevance of *worn piston rings* to *low oil level*, then *oil leak* and all its ancestors fall into the category of nuisance nodes and can be reduced.

The above methods do not alter the quantitative properties of the underlying graph and are, therefore, exact. In addition, for a collection of evidence nodes e and a node of interest t, there will usually be nodes in the BBN that are only marginally relevant for computing the posterior probability distribution of t. Identifying nodes that have non-zero but small impact on t and pruning them can lead to a further simplification of the graph with only a slight impact on the precision of the conclusions. To identify such nodes, one needs a suitable metric for measuring changes to the distribution of t, as well as a threshold beyond which changes are unacceptable. Such metrics can be derived solely from the probabilities (e.g., cross entropy), or from decision and utility models involving the distribution of t. In INSITE, a system that generates explanations of BBN inference, Suermondt [24] found cross entropy to be the most practical measure. Use of such a metric and threshold allows us to discriminate between more and less influential evidence nodes, and to identify nodes and arcs in the BBN that might, for practical purposes, be omitted from computations and from explanations of the results.

Relevance in probabilistic models has a natural interpretation and probability theory supplies effective tools that aid in determining what is at any given point most crucial for the inference. The common denominator of the above methods is that they are theoretically sound and quite intuitive. They are exact or, as it is the case with the last method, they come with an apparatus for controlling the degree of approximation, preserving correctness of the reduced model.

5 QUALITATIVE REASONING

Probabilistic reasoning schemes are often criticized for the undue precision they require to represent uncertain knowledge in the form of numerical probabilities. In fact, such criticism is misconceived since probabilistic reasoning does not need to be conducted with a full numerical specification of the joint probability distribution over a model's variables. Useful conclusions can be drawn from merely constraints on the joint probability distributions. The reasoning about relevance, described in the previous section, is often purely qualitative, based only on the structure of the directed probabilistic graph. Another instance of qualitative probabilistic reasoning can be obtained by amending reasoning about relevance with reasoning about its sign.

Wellman introduced a qualitative abstraction of BBNs, known as Qualitative Probabilistic Networks (QPNs)[26]. QPNs share the structure with BBNs, but instead of numerical probability distributions, they represent the signs of interactions among variables in the model. A proposition a has a positive *influence* on a proposition b, if observing a to be true makes b more probable. QPNs generalize straightforwardly to multivalued and continuous variables. QPNs can replace or supplement quantitative Bayesian belief networks where numerical probabilities are either not available or not necessary for the questions of interest. An expert may express his or her uncertain knowledge of a domain directly in the form of a QPN. This requires significantly less effort than a full numerical specification of a BBN. Alternatively, if we already possess a numerical BBN, then it is straightforward to identify the qualitative relations inherent in it, based on the formal probabilistic definitions of the properties. QPNs determine the effect of observations on the probability of a variable of interest and are useful for structuring planning problems. If a graph contains decision nodes and a value node, queries concerning the sign of influences can be used to identify dominating decision options [26]. Figure 2 shows a QPN for the example of Figure 1.

Henrion and I [8] have shown that reasoning in QPNs can be conducted in polynomial time by proposing a computationally efficient algorithm for reasoning in QPNs. This

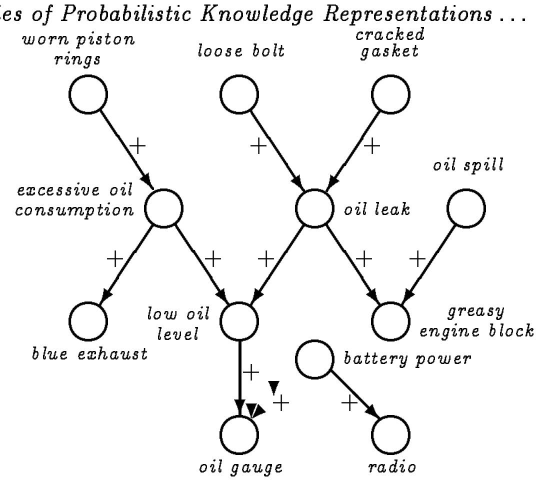

Fig. 2. An example of a qualitative probabilistic network

algorithm, called *qualitative belief propagation*, traces the effect of an observation e on other graph variables by propagating the sign of change from e through the entire graph. Every node t in the graph is given a label that characterizes the sign of impact of e on t. In this way, once the propagation is completed, one can easily read off the labeled graph how exactly the evidence impacts t, i.e., what are the intermediate nodes through which e acts on t.

This algorithm has d-separation implicitly built into it and can address the problem of structural relevance. In order to achieve this, use the algorithm to compute the qualitative impact of a variable of interest t given an evidence variable e. The algorithm marks in this case each node n in the graph with the sign of influence of t on n. All nodes that are marked '0 in propagation of a non-zero sign from t are structurally not relevant for t given e.

If the signs of impact of two pieces of evidence e_1 and e_2 on a node t are different, we are dealing with conflicting evidence. We speak about conflicting evidence also when an evidence variable e impacts t positively through one path and negatively through another. The labels placed on each node in the graph by the qualitative belief propagation algorithm allows a computer program, in case of sign-ambiguity, to reflect about the model at a meta level and find the reason for ambiguity, for example, which paths are in conflict. Hence, it can suggest ways in which the least additional specificity could resolve the ambiguity.

6 FROM PROBABILITY TO LOGICS

One way of looking at models of uncertain domains is that they describe a set of possible states of the world. This view is explicated by the logic-based approaches to reasoning under uncertainty — at any given point various extensions of the current body of facts are possible, one of which, although unidentified, is assumed to be true. Since the number of possible extensions of the facts is exponential in the number of uncertain variables in the model, it seems to be intuitively appealing, and for sufficiently large domains practically necessary, to limit the number of extensions considered. Several artificial intelligence schemes for reasoning under uncertainty, such as case-based or script-based reasoning, abduction, or non-monotonic logics, seem to be following this path.

I have demonstrated [5] that the probabilities of individual states of the model can be expected to be drawn from highly skewed lognormal distributions. The probability mass carried by the individual states follows qualitatively the same distribution, but it is usually strongly shifted towards higher probability values and is cut off at the point $p = 1.0$. The asymmetry in individual prior and conditional probability distributions determines the variance in the distribution of probabilities of single states (probabilities of states are spread over many orders of magnitude) and also determines the magnitude of the shift towards the higher values of probabilities. For sufficiently asymmetric distributions (i.e., for distributions describing well known systems), a small fraction of states can be expected to cover a large portion of the total probability space with the remaining states having practically negligible probability. In the limit, when there is no uncertainty, one single state covers the entire probability space.

The more we know about a domain, the more asymmetry individual conditional probabilities will show. When the domain and its mechanisms are well known, probability distributions tend to be extreme. This implies a large variance and a large shift in the expected contribution function and, therefore, a small number of very likely states of the model. This makes intuitive sense — we tend to act with confidence in environments that we know well, just because we can easily predict what will happen. When an environment is less familiar, the probability distributions tend to be less extreme, there is less variance in probabilities. The shift in contribution function is small and none of the states is very likely. Figure 3 shows theoretically derived probability density functions for two models consisting of ten binary variables, in which individual conditional probability distributions were 0.2 and 0.8 (left diagram) and 0.3 and 0.7 (right diagram). The ordinate is in logarithmic scale — the lognormal distributions found in practical models tend to span over many orders of magnitude and are extremely skewed, making them unreadable in linear scale.[3] Note that the distribution pictured in the right diagram is for a system with more symmetry in the distribution, i.e., a system that we know less about. In this case, the shift towards higher probabilities is small, most states will have low probabilities and, hence, no very likely states will be observed.

The left diagram in Figure 4 shows the theoretically derived relationship for a model consisting of ten binary variables with probability distributions drawn uniformly from the intervals $[0, 0.1]$ and $[0.9, 1.0]$. Please, note that the distribution of the contributions of probabilities of states to the total probability mass is strongly shifted towards higher probabilities and cut off at point $\log p = 0$. The right diagram in Figure 4 shows the result of a simulation in which an uncertain model satisfying the assumption was randomly created and then its joint probability distribution analyzed. This simulation was done in

[3] This and other figures use decimal rather than natural logarithm because of the ease with which we can translate the value of the decimal logarithm to order of magnitude in the decimal system.

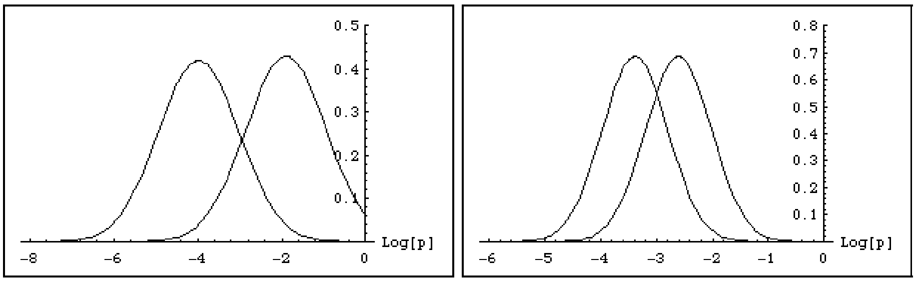

Fig. 3. Theoretically derived distributions for identical conditional probability distributions for 10 binary variables with probabilities of outcomes equal to 0.2 and 0.8 (left diagram) and 0.3 and 0.7 (right diagram).

the spirit of a demonstration device similar to those proposed by Gauss or Kapteyn to show a mechanism by which a distribution is generated. Similarity of the theoretically derived distributions to the simulation results, even for as few as 10 random variables, is apparent.

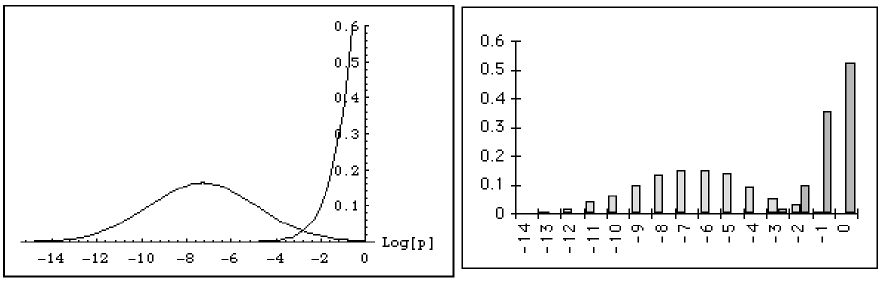

Fig. 4. Identically distributed conditional probability distributions for 10 binary variables with probabilities of outcomes drawn uniformly from the intervals $[0, 0.1]$ and $[0.9, 1.0]$: theoretically derived probability distribution over probabilities of states of the joint probability distribution and the distribution of their contribution to the probability mass (left diagram) and the histograms observed in a simulation (right diagram).

A stronger support for this analysis comes from studying the properties of a real model. The most realistic model with a full numerical specification that was available to me was ALARM, a medical diagnostic model of monitoring anesthesia patients in intensive care units [1]. With its 38 random variables, each having two or three outcomes, ALARM has a computationally prohibitive number of states. I selected, therefore, several self-contained subsets of ALARM consisting of 7 to 13 variables, and analyzed the distribution of probabilities of all states within those subsets. Figure 5 shows the result of one of such run, identical with the results of all other runs with respect to the form of the ob-

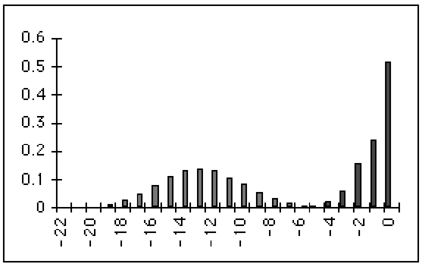

Fig. 5. Histograms of the probabilities of various states (the bell-shaped curve) and their contribution to the total probability mass (the peak on the right side) for a subset of 13 variables in the ALARM model.

served distribution. It is apparent that the histogram of states appears to be for normally distributed variables, which, given that the ordinate is in logarithmic scale, supports the theoretically expected lognormality of the actual distribution. The histogram also indicates a small contribution of its tail to the total probability mass. The subset studied contained 13 variables, resulting in 525,312 states. The probabilities of these states were spread over 22 orders of magnitude. Only the most likely states, spread over the first five orders of magnitude, provided meaningful contribution to the total probability mass. Of all states, there was one state with probability 0.52, 10 states with probabilities in the range $(0.01, 0.1)$ and the total probability of 0.23, and 48 states with probabilities in the range $(0.001, 0.01)$ and the total probability of 0.16. The most likely state covered 0.52 of the total probability space, the 11 most likely states covered 0.75 of the total probability space, and the 59 most likely states (out of the total of 525,312) covered 0.91 of the total probability space.

The above result gives some insight into the logic-based schemes for reasoning under uncertainty, showing when and why they will work and when they will not perform too well. In the domains that are well known, there will be usually a small number of very likely states and these states can be modeled in logic. In the domains that contain much uncertainty, logic-based approaches will fail: there will be many plausible states and commitment to any of them is likely to be suboptimal.

7 HUMAN INTERFACES

Decision analysis, which is the art and science of applying decision theory to aid decision making in the real world, has developed a considerable body of knowledge in model building, including elicitation of the model structure and elicitation of the probability distribution over its variables. These methods have been under a continuous scrutiny of psychologists working in the domain of behavioral decision theory and have proven to cope reasonably well with the dangers related to human judgmental biases. Also, at the output side, the approach taken by decision analysis is compatible with that of intelligent systems. The goal of decision analysis is providing insight into the decision. This insight, consisting of the analysis of all relevant factors, their uncertainty, and criticality of some assumptions, is even more important than the actual recommendation.

Probability theory is known to model well certain patterns of human plausible reasoning, such as mixing predictive and diagnostic inference, discounting correlated sources of evidence, or intercausal reasoning [9, 13, 16]. BBNs offer several advantages for automatic generation of explanation of reasoning to the users of intelligent systems. As they encode the structure of the domain along with its numerical properties, this structure can be analyzed at different levels of precision. The ability to derive lower levels of specification and, therefore, changing the precision of the representation makes probabilistic models suitable for both computation and explanation. Soundness of the reasoning procedure makes it easier to improve the system, as explanations based on a less precise abstraction of the model provide an approximate, but correct picture of the model. Possible disagreement between the system and its user can always be reduced to a disagreement over the model. This differs from the approach taken by some alternative schemes for reasoning under uncertainty, where simplicity is achieved by making simplifying, although not always substantiated assumptions (such as independence assumptions embedded in Dempster–Shafer theory and possibility theory) [27]. Ultimately, it is hard to determine in these schemes whether possibly wrong advice is the result of errors in the model or errors in the reasoning procedure.

Qualitative belief propagation, presented in Section 5, appears to be easy to follow for people and it can be used for generation of verbal explanations of probabilistic reasoning. The individual signs along with the signs of influences can be translated into natural language sentences describing paths of change from the evidence to the variable of interest. Explanation of each step involves reference to a usually familiar causal or diagnostic interaction of variables. In general, explanations based on qualitative reasoning are easier to understand than explanations using numerical probabilities. So even where a quantified BBN is available, it may often be clearer to reduce it to the qualitative form, and base explanations on purely qualitative reasoning. An example of a qualitative belief propagation-based explanation is given in Figure 6. More details on generation of verbal explanations of reasoning based on belief propagation can be found in [4, 7, 15, 16]. Suermondt [24] provides a thorough quantitative treatment of several issues that are complementary to the QBP explanations.

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Qualitative influence of greasy engine block on excessive oil
consumption:
Greasy engine block is evidence for oil leak.
Oil leak explains low oil level, hence is evidence against
excessive oil consumption.
Therefore, greasy engine block is evidence against excessive
oil consumption.
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Fig. 6. Qualitative explanations: An example.

Another method for generating explanations is based on the observation that in most models there is usually a small number of very likely states (this was discussed in Section 6). If there is a small number of very likely states, most likely states of the model can be identified and presented to the user. This is the essence of *scenario-based explanations* [4, 6, 16]. An example of a scenario-based explanation is given in Figure 7.

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The observed low oil level can be caused by excessive oil consumption
or by oil leak.

Scenarios supporting excessive oil consumption are:
1. There is no oil leak, excessive oil consumption causes low oil
level (p=0.35).
2. Cracked gasket causes oil leak, excessive oil consumption and oil
leak cause low oil level (p=0.15).
3. Other, less likely scenarios (p=0.05).

Scenarios disproving excessive oil consumption are:
1. Cracked gasket causes oil leak, there is no excessive oil
consumption, oil leak causes low oil level (p=0.36).
2. Loose bolt causes oil leak, there is no excessive oil consumption,
oil leak causes low oil level (p=0.04).
3. Other, less likely scenarios (p=0.05).

Therefore, excessive oil consumption is more likely than not (p=0.55).
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Fig. 7. Scenario-based explanations: An example.

8 CONCLUSION

I have discussed five issues related to the foundations of intelligent systems research and have shown that they are addressed adequately by probabilistic knowledge representations. The view that probability theory is a numerical scheme, difficult to comprehend for humans, requiring a prohibitive number of expert judgments, and demanding high computational power seems to be misplaced. Probability theory is based on sound qualitative foundations that allow for capturing the essential properties of a domain, along with its causal structure. Directed probabilistic graphs model explicitly independences and tie probability with causality, allowing for a concise and insightful representation of uncertain domains. Probabilistic knowledge representations and reasoning do not need to be quantitative — there is a whole spectrum of possible levels of specifying models, ranging from independence or relevance to full numeric specification. The amount of specificity in a model can be made dependent on available information and a reasoning agent can dynamically move between different levels of specification to do the most with the least possible effort. Concepts such as relevance and conflicting evidence have a natural, formally sound meaning. Finally, probabilistic knowledge representations directly support user interfaces. Their structural properties make it possible to refer to the causal structure of the domain. Full numerical specification of a domain, if available, allows for manipulating with the level of precision for the sake of simplification. It is possible to generate efficient explanations of probabilistic inference in intelligent systems.

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