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# Book Review

# Judea Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference**

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## Introductory remarks

Judea Pearl's book, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, offers a comprehensive and coherent discussion of the important results of the Renaissance of the probabilistic approach to reasoning under uncertainty in AI. It is a book for which the author should be highly credited. Pearl has dedicated himself to presenting all aspects of a graph representation of the Bayesian probabilistic inference constituted by the belief-network formalism. He has accomplished this goal by providing the reader with a complete background for the formalism, by presenting the central issues, and by extending the scope smoothly to cover decision analysis and structural learning. Finally, Pearl relates this approach to other probabilistic (non-Bayesian) formalisms for handling uncertainty in AI.

Although the book is certainly not easy to read, especially for people who want to understand the full details of the subject, the casual reader can grasp the essence of the probabilistic approach to uncertainty in AI. To get the full benefit of the book, the reader should follow the author's advice on how to tackle the text, which is given in terms of the reader's background.

* (Morgan Kaufmann, San Mateo, CA, 1988); xix + 552 pages.

**The Renaissance of probabilistic reasoning in AI**

The Bayesian probabilistic view, which is essential for this book, is founded on the fundamental premise that all uncertainties can be represented and measured as probabilities. The primary justification for this premise lies in the formal, axiomatic development of the normative framework for rational behavior of individuals, in the face of uncertainty. Any individual, desiring to behave (at least in principle) in this way, is led to act as though his/her uncertain knowledge is represented using subjective probability.

Beginning in the mid-1970s, the coherent use of probabilities was abandoned for nearly a decade as a vehicle for reasoning under uncertainty in AI. To follow a normative probabilistic approach in uncertainty management, investigators essentially made a choice between oversimplified domain models, where a high degree of independence among variables was required, and computationally intractable domain models, described by the full joint of probabilities. Neither of these alternatives satisfied the requirement of the AI community for a knowledge language, rich enough in its semantics to handle uncertainty. Furthermore, the first alternative was too simplistic for real-world cases, whereas the second was combinatorially explosive in the acquisition of the probabilities as well as in the inference.

Instead, new calculi, such as the MYCIN certainty-factor, became popular. This calculus was fitted to the modularity of rule-based systems; however, the cost for the computational convenience of this calculus, when interpreted in the framework of probabilities, was that the normative validity was limited to simple tree-structured rule bases where no evidence supported more than one hypothesis.

Against this backdrop, in the early 1980s, Pearl laid the basis for circumventing those difficulties by introducing the AI community to a paradigm combining the belief-network knowledge representation and the Bayesian probabilistic updating scheme. This formalism provided the semantics for constructing domain models, which was missing in the earlier use of probabilities in AI. Through the topology of the graphical representation, it was possible precisely to describe dependencies and independencies among domain variables, and to utilize this description through an efficient, normative, and conceptually meaningful updating scheme. The use of probabilities in AI was thus brought out of its Middle Ages.

Pearl's book is a review of an astonishing amount of research that has as its backbone the belief-network paradigm. The kernel is half a dozen of the author's articles, already published in this journal. There is a clear commitment to exploit and defend to the extent possible the point that the Bayesian statistics combined with the semantics of the belief network offer the AI community an operational framework that goes beyond the traditional view of probabilities.

**Belief networks: a short introduction to the central concept**

A belief network as a domain model is essentially a graph consisting of nodes and arcs. The semantics of the nodes is domain concepts or domain variables, and the semantics of the arcs is the interactions between these nodes, described as conditional probabilities. Unfortunately, the literature does not maintain a consistent naming convention for belief networks, so several synonyms are used (see p. 13 in Pearl's book). More names can be added to that list, such as *probabilistic influence diagram* and *causal probabilistic net.*

To give the flavor of the type of inference we can accomplish with the belief-network methodology, we illustrate a simple network in Fig. 1. This example is taken from the book (p. 56 and Fig. 10.6, p. 503). Here proposition $A$, "The grass is wet" can be caused either by $C_1$, "It rained last night", or by $C_2$, "The sprinkler was on", and we can observe that $O_1$, "The grass is cold and shiny", or $O_2$, "My shoes are wet", could be caused by $A$. The semantics of the network reveals that $C_1$ and $C_2$ are conditionally dependent given $A$, and that $O_1$ and $O_2$ are conditionally independent given $A$. The prior and conditional probabilities, $p(C_1)$, $p(C_2)$, $p(A \mid C_1, C_2)$, $p(O_1 \mid A)$, and $p(O_2 \mid A)$ are assumed to be known, and the variables are either true or false.

One aspect of the probabilistic inference is exemplified in the following scenario: If the belief in $A$ is updated by observation of $C_2$, our belief in $C_1$ does not change from the prior value; $C_1$ and $C_2$ are independent; however if the belief in $A$ on the other hand is updated by observation of $O_1$ or $O_2$, then $C_1$ and $C_2$ will become dependent. That is, if we again observe $C_2$, the updating algorithm will change the belief in $C_1$ accordingly. The probability that "it rained last night" will decrease and the observation that "the sprinkler was on" is a plausible explanation for "the grass is wet". Although it is an over-simplified model, the scenario illustrates the point that the inference realizes changes between dependency and independency for pairs of variables as a built-in feature.

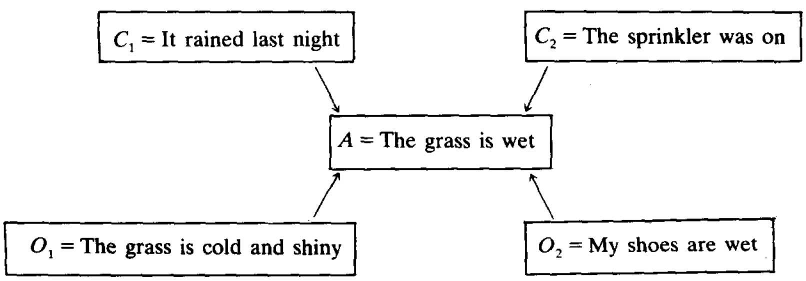


Fig. 1. An example of a simple belief network.

## The form

Based on the solid foundation of the Bayesian assumptions, Pearl has developed an inference scheme for propagation of beliefs in a singly connected belief network. The common thread throughout the book is this scheme, where every action is locally scoped and autonomous, and where the formalism inherently distinguishes between *causal* and *evidential* reasoning support. The book builds up the arguments and the apparatus for using the belief network as a knowledge-representation scheme; when the reader is thus prepared, the author carefully presents the propagation scheme. No matter what relation the reader had to the Greek letters pi and lambda before reading the book, Pearl makes sure that these letters, in the mind of the reader, will be associated strongly with the two essential concepts in the formalism: the local propagation of causal and evidential information, respectively.

The readability of the inference scheme has been enhanced greatly over the years since Pearl first presented it. This scheme is the core of the book, and Pearl communicates it clearly to the reader, regardless of the reader's background. With this foundation, Pearl systematically guides the reader through all aspects of using the inference algorithm, focusing on current research within this field.

Pearl's platform is the intentional approach to uncertainty in AI, in which, technically speaking, uncertainty is a built-in feature of the modeling tool used to describe a domain. This perspective is contrary to the extensional approach, where the uncertainty is attached to model components and is combined by a mechanism not inherently belonging to the knowledge-representation paradigm employed.

The text contains clarifying examples that highlight the capability and power of the belief-network approach; a few of them will become quite familiar to the reader by the end of the book. For example, Tweety has survived this book as well. However, the reader must be alert to get a sense of the characteristics of problems that the formalism is less capable of handling. The examples are typical for a book with an underlying theoretical trait; that is, they are made as simple as possible to illustrate a certain problem, but fail to give the reader a feeling of real-world applications. More insight into the pitfalls the reader would face when using the graph language to model complex problems would have increased the value of the discussion.

Pearl explores the calculus of plausible inference in great detail, to illustrate that the tool at hand is superior, and it is difficult to point out any aspect on which he does not touch. A reader who has explored all the corners of this book will have the necessary tools and the background for constructing practical applications, utilizing the best of this paradigm. When it comes to formalizing the problems in the real world, however, the reader will be essentially on his or her own.

The reader could easily be left with the impression that most problems can be represented by a singly connected network. The reality is that single connectivity is often a too coarse model approximation. Pearl claims that his presentation is made with computational feasibility in mind, but although implementation of the basic actions can be done easily from the book, many practical issues, essential to get real systems running efficiently, are not discussed. Issues involving computational complexity are not the subject of this book.

The presentation of alternative views is restricted to those that are claimed to belong to the family of probabilistic approaches. There is a clear bias toward the Bayesian perspective in the treatment of the non-Bayesian probabilistic formalisms for handling uncertainty.

When all the features of the paradigm are presented, it is important that the reader keep in mind the basic philosophy of the author:

> We take for granted that probability calculus is unique in the way it handles context-dependent information and that no competing calculus exists that closely covers so many qualitative aspects of plausible reasoning. So the calculus is worthy of exploitation, emulation, or at the very least, serious exploration. We therefore take probability calculus as an initial model of human reasoning from which more refined models may originate, if needed. By exploring the limits of using probability calculus in machine implementations of plausible inference, we hope to identify conditions under which extensions, refinements, and simplifications are warranted. (p. 20)

One of the intentions of the book is to show that the probabilistic paradigm, built on a concept that is several hundred years old, adds power to the pool of techniques available to automate the human task of solving complex problems. Indeed Pearl succeeds in this task. Readers with a nonmathematical or nonstatistical background will probably find it difficult to penetrate the barrier between the "asterisk" sections and the "nonasterisk" sections—asterisks being the author's indication of a pathway.

The book is a valuable reference for the field of belief-network reasoning, and is a "must" for researchers in this field. What makes the book useful for a broader audience too, is the way the author has wrapped discussions, arguments, and examples of the use of probabilities around this research, achieving his goal of advocating the probabilistic method by constantly stressing the paradigm's compatibility with human reasoning.

The author has intended to make the book readable for a multilevel audience, and the reader should be prepared for a change in the flavor of different sections from purely philosophical to highly technical. This style maps well the dynamics of the author, but may give the reader trouble. As already mentioned, part of the material is not easily accessible. Each chapter begins, to a lesser or greater extent, with a general discussion, and Pearl has done a good job in bridging discussions in picturesque language to the more stringent, mathematical, and axiomatic formulation of the major part of most chapters. This feature makes certain sections of the book eligible for use in courses, provided that the students' mathematical knowledge is adequate.

## The contents

The book has 10 chapters. Each contains a few pages of bibliographical and historical remarks, as well as exercises (for which no answers are provided). At the back of the book is an 18-page bibliography, a five-page author index, and a seven-page subject index.

In the first chapter, Pearl clearly answers the question "Why probabilities?" by reviewing a few essential issues, such as causality (phrased in a pragmatic way as a practical computational device), bidirectional reasoning, and explaining away, all of which are pursued through the rest of the book; probability is something other than the manipulation of numbers.

The two ingredients needed to set the scene for the belief propagation—the machinery of Bayesian inference and the foundation for graphical representations—are the subjects of Chapters 2 and 3. The author tries to pinpoint what can be modeled in the unification of graph-based knowledge representation and Bayesian inference techniques using Markov networks and Bayesian networks: What emerges is a comprehensive picture of the expressiveness—or lack thereof—of modeling dependencies and independencies. The key to understanding the language of graphs, used to express a domain model, is a clear notion of the explicit versus the implicit expressiveness of this tool for formalizing knowledge.

Chapter 4 is devoted to the local belief-updating paradigm in belief networks. This pivotal chapter is self-contained, as though the reader was climbing up the ladder from updating beliefs in simple tree structures to dealing in complex ways with multiple paths (loops) in networks. The calculus is outlined carefully, and the basic algorithms for using the belief network are deduced, to provide a consistent set of beliefs when new evidence has been absorbed. In this chapter, Pearl is casting his tool.

With the tool at hand, Pearl adds different aspects to the use of the local updating paradigm in the following four chapters.

Chapter 5 deals with the handling and explaining of belief commitment, and explains how this fits with the autonomous message-passing scheme. Once more, Pearl uses the opportunity to anchor the basic propagation concepts. In Chapter 6, belief-network representation is extended to influence diagrams: that is, a new type of nodes is added that represents a decision, based on utility functions. The connection to the field of decision theory is made, and the class of problems the extended paradigm can handle is expanded. This extension is consistently related to local belief propagation.

Chapter 7 adds further items to the list of means to utilize the local updating. First, taxonomic hierarchies are viewed from the belief-network paradigm, then the handling of continuous variables within the same framework is described, and, finally, Pearl focuses on second-order probabilities and argues that this concept already is a built-in feature of the Bayesian approach. Pearl has moved from the central core of the methodology outward, expanding the territory of probabilities, and here he enters an area where the arguments become more controversial.

Up to this point, the knowledge-acquisition process has not been addressed at all; however, the possibility for structural learning from data (joint probabilities) is the subject of Chapter 8. Unfortunately, only simple structures, such as trees, seem to be feasible objects for structural learning with the current state of the art, so structural learning does not solve the problems of knowledge acquisition.

In Chapter 9, Pearl boils down the major difference between the Bayesian-based methodology and the Dempster–Shafer technique, which is also based on probability theory, to the degree that they handle models that are not fully specified. Whereas the Bayesian approach basically requires a complete specification, the Dempster–Shafer technique for handling uncertainty is characterized by computing the probability of extensions to models that are not completely specified. The applicability of the different approaches is certainly dependent on the type of problem to which the technique is applied; the major example, in this chapter—the three-prisoner problem—is well within the territory of Bayesian reasoning.

The final chapter (Chapter 10) establishes a bridge between probability and logic. Pearl extends nonmonotonic logic to causal–evidential logic, which recognizes the bidirectional reasoning scheme (the foundation of the book), although it lacks the soft nature of expression that the probabilities allow for. The story is closed by a dialogue between a probabilist and a logician that gives the reader new perspectives on causality, commitment, and dependencies.

## Summary

In conclusion, in the past decade, a large part of the AI community has disregarded the use of probabilities. This book knocks the breath out of the arguments against probability from these days, and proves that the probabilistic approach can be used to build real AI systems. The mission of this book is to collect the research that lays the foundation of a new era of probabilistic inference. Pearl has developed a coherent story from these different projects.

The book is a landmark in the landscape of probabilistic reasoning, and already provides an anchor for new research within this field. This book will definitely remain valid as a reference in the future given its multilevel readability; however, considering the potential applicability, this text is probably only the first of several monographs on this subject.

Readers, who are shopping for methods to be adapted in the practical construction of AI systems, may regard this book as a reference manual for the probabilistic approach. The process of constructing and formalizing domain knowledge in this probabilistic language, however, is not something that readers can simply look up in the index: they must synthesize the material themselves.