

Information Science and Statistics

Uffe B. Kjaerulff • Anders L. Madsen

# Bayesian Networks and Influence Diagrams

A Guide to Construction  
and Analysis



Springer

# **Information Science and Statistics**

*Series Editors:*

M. Jordan

J. Kleinberg

B. Schölkopf

# Information Science and Statistics

---

*Akaike/Kitagawa:* The Practice of Time Series Analysis

*Bishop:* Pattern Recognition and Machine Learning

*Cowell/Dawid/Lauritzen/Spiegelhalter:* Probabilistic Networks and Expert Systems

*Doucet/de Freitas/Gordon:* Sequential Monte Carlo Methods in Practice

*Fine:* Feedforward Neural Network Methodology

*Hawkins/Olwell:* Cumulative Sum Charts and Charting for Quality Improvement

*Jensen/Nielsen:* Bayesian Networks and Decision Graphs, Second Edition

*Kjærulff/Madsen:* Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis

*Lee/Verleysen:* Nonlinear Dimensionality Reduction

*Marchette:* Computer Intrusion Detection and Network Monitoring: A Statistical Viewpoint

*Rissanen:* Information and Complexity in Statistical Modeling

*Rubinstein/Kroese:* The Cross-Entropy Method: A Unified Approach to Combinatorial Optimization, Monte Carlo Simulation, and Machine Learning

*Studeny:* Probabilistic Conditional Independence Structures

*Vapnik:* The Nature of Statistical Learning Theory, Second Edition

*Wallace:* Statistical and Inductive Inference by Minimum Message Length

Uffe B. Kjærulff • Anders L. Madsen

# Bayesian Networks and Influence Diagrams

A Guide to Construction and Analysis

Uffe B. Kjærulff  
Department of Computer Science  
Aalborg University  
Selma Lagerlöfs Vej 300  
DK-9220 Aalborg  
Denmark  
uk@cs.aau.dk

Anders L. Madsen  
HUGIN Expert A/S  
Gasværksvej 5  
DK-9000 Aalborg  
Denmark  
anders@hugin.com

### *Series Editors*

Michael Jordan  
Division of Computer Science  
and Department of Statistics  
University of California, Berkeley  
Berkeley, CA 94720  
USA

Jon Kleinberg  
Department of Computer Science  
Cornell University  
Ithaca, NY 14853  
USA

Bernhard Schölkopf  
Max Planck Institute  
for Biological Cybernetics  
Spemannstrasse 38  
72076 Tübingen  
Germany

ISBN: 978-0-387-74100-0

e-ISBN: 978-0-387-74101-7

DOI: 10.1007/978-0-387-74101-7

Library of Congress Control Number: 2007940536

© 2008 Springer Science+Business Media, LLC

All rights reserved. This work may not be translated or copied in whole or in part without the written permission of the publisher (Springer Science+Business Media, LLC, 233 Spring Street, New York, NY 10013, USA), except for brief excerpts in connection with reviews or scholarly analysis. Use in connection with any form of information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed is forbidden.

The use in this publication of trade names, trademarks, service marks, and similar terms, even if they are not identified as such, is not to be taken as an expression of opinion as to whether or not they are subject to proprietary rights.

Printed on acid-free paper

9 8 7 6 5 4 3 2 1

springer.com

*To our wives and children*

---

## Preface

This book is a monograph on practical aspects of probabilistic networks (a.k.a. probabilistic graphical models) and is intended to provide a comprehensive guide for practitioners that wish to understand, construct, and analyze decision support systems based on probabilistic networks, including a number of different variants of Bayesian networks and influence diagrams. The book consists of three parts:

- *Part I: Fundamentals* of probabilistic networks, including Chapters 1–5, covering a brief introduction to probabilistic graphical models, the basic graph-theoretic terminology, the basic (Bayesian) probability theory, the key concepts of (conditional) dependence and independence, the different varieties of probabilistic networks, and methods for making inference in these kinds of models. This part can be skipped by readers with fundamental knowledge about probabilistic networks.
- *Part II: Model construction*, including Chapters 6–8, covering methods and techniques for elicitation of model structure and parameters, a large number of useful techniques and tricks to solve commonly recurring modeling problems, and methods for constructing probabilistic networks automatically from data, possibly through fusion of data and expert knowledge. Chapters 6 and 7 offer concrete advice and techniques on issues related to model construction, and Chapter 8 explains the theory and methods behind learning of Bayesian networks from data.
- *Part III: Model analysis*, including Chapters 9–11, covering conflict analysis for detecting conflicting pieces of evidence (observations) or evidence that conflicts with the model, sensitivity analysis of a model both with respect to variations of evidence and model parameters, and value of information analysis. This part explains the theory and methods underlying the three different kinds of analyses.

Probabilistic networks have become an increasingly popular paradigm for reasoning under uncertainty, addressing such tasks as diagnosis, prediction, decision making, classification, and data mining. From its infancy in the mid-

1980s till today there has been a rapid development of algorithms for construction, inference, learning, and analyses for probabilistic networks, and since the turn of the millennium there has been a steep increase in the number of new applications of probabilistic networks. Its popularity stems from a number of factors. The graphical-based language for probabilistic networks is a powerful tool for expressing causal interactions while in the same time expressing dependence and independence relations among entities of a problem domain. Being graphical and compact the language furthermore provides an excellent intuitive means of communication of ideas among knowledge engineers and problem domain experts. Although inference in complex probabilistic networks can be quite demanding (or even intractable), the fact that inference can be performed efficiently in models of hundreds or even thousands of variables is another contribution to the popularity of probabilistic networks. Another important factor is that inference in probabilistic networks is based on a well-established theoretical foundation of probability calculus and decision theory, and hence provides mathematically coherent methods for deriving conclusions under uncertainty, where multiple sources of information and complex interaction patterns are involved. The existence of efficient algorithms for learning and adaptation of probabilistic networks from data and the possibility of fusing data and expert knowledge are yet other attractive features. Finally, probabilistic networks are “white boxes” in the sense that the model components (variables, links, probability and utility parameters) are open to interpretation, which makes it possible to perform a whole range of different analyses of the networks (e.g., conflict analysis, (in)dependence analyses, sensitivity analysis, and value of information analysis).

As mentioned above, this book takes a practical outset, and is intended primarily for those who wish to construct and analyze probabilistic networks without necessarily having a deep understanding neither of the underlying theory and methods for inference, learning, analyses, etc. nor of alternative paradigms for reasoning under uncertainty. Hence, the scope of this book is quite narrow, focusing almost exclusively on issues relevant for understanding, constructing, and analyzing the different variants of Bayesian networks and influence diagrams. Other methods for inference and decision making under uncertainty, therefore, get very limited attention.

The intended audience of this book is practitioners rather than students of artificial intelligence. Despite this fact, exercises have been included in all chapters (except Chapter 1) for the reader to check his/her level of understanding. Answers to selected exercises and more can be found at <http://developer.hugin.com/Publications/BNID/>.

For a quick overview, the different kinds of probabilistic network models considered in this book can be characterized very briefly as follows:

- *Discrete Bayesian networks* represent factorizations of joint probability distributions over finite sets of discrete random variables. The variables are represented by the nodes of the network, and the links of the network



represent the properties of (conditional) dependences and independences among the variables. For each variable is specified a set of local probability distributions conditional on the configuration of its conditioning (parent) variables.

- *Conditional linear Gaussian (CLG) Bayesian networks* represent factorizations of joint probability distributions over finite sets of random variables where some are discrete and some continuous. Each continuous variable is assumed to follow a linear Gaussian distribution conditional on the configuration of its discrete parent variables.
- *Discrete influence diagrams* are (discrete) Bayesian networks augmented with (discrete) decision variables and (discrete) utility functions. An influence diagram is capable of computing expected utilities of various decision options given the information known at the time of the decision.
- *Conditional linear-quadratic Gaussian (CLQG) influence diagrams* combine CLG Bayesian networks, discrete influence diagrams, and quadratic utility functions into a single framework supporting decision making under uncertainty with both continuous and discrete variables.
- *Limited-memory influence diagrams (LIMIDs)* relax two fundamental assumptions of influence diagrams: the no-forgetting assumption implying perfect recall of past observations and decisions, and the assumption of a total order on the decisions. LIMIDs allow us to model more types of decision problems than the ordinary influence diagrams.
- *Object-oriented probabilistic networks* are hierarchically specified probabilistic networks (i.e., one of the above), allowing the knowledge engineer (model builder) to work on different levels of abstraction, as well as exploiting the usual concepts of encapsulation and inheritance known from object-oriented programming paradigms.

The book provides numerous examples, hopefully helping the reader to gain a good understanding of the various concepts, some of which are known to be hard to understand at a first encounter.

Even though probabilistic networks provide an intuitive language for constructing knowledge-based models for reasoning under uncertainty, knowledge engineers can often benefit from a deeper understanding of the principles underlying these models. For example, knowing the rules for reading statements of dependence and independence encoded in the structure of a network may prove very valuable in evaluating whether the network correctly models the dependence and independence properties of the target problem. This, in turn, may be crucial to achieving, for example, correct posterior probability distributions from the model. Also, having a basic understanding of the relations between the structure of a network and the complexity of inference may prove useful in the model construction phase, avoiding structures that are likely to result in problems of poor performance of the final decision support system.

We present such basic concepts, principles, and methods underlying probabilistic models that practitioners need to acquaint themselves with.

In Chapter 1, we provide a bit of background and contextual introduction to Bayesian networks and influence diagrams. To give the reader a first understanding of probabilistic networks, we present a very simple Bayesian network and shown how it can be augmented with explicit representation of decision options and a utility function, turning it into an influence diagram. Also, we discuss briefly the notions of causality, construction of probabilistic networks, and applicability (i.e., when to use probabilistic networks).

In Chapter 2, we describe the fundamental concepts of the graphical language used to construct probabilistic networks as well as the rules for reading statements of (conditional) dependence and independence encoded in network structures. We present two equivalent criteria for reading these statements, namely Pearl's (Pearl 1988) d-separation criterion and the criterion of directed Markov property by Lauritzen, Dawid, Larsen & Leimer (1990a).

In Chapter 3, we present the uncertainty calculus used in probabilistic networks to represent the numerical counterpart of the graphical structure, namely classical (Bayesian) probability calculus. We shall see how a basic axiom of probability calculus leads to recursive factorizations of joint probability distributions into products of conditional probability distributions, and how such factorizations along with local statements of conditional independence naturally can be expressed in graphical terms.

In Chapter 4, we see how putting the basic notions of Chapters 2 and 3 together we get the notion of discrete Bayesian networks. Also, we present a range of derived types of network models, including conditional Gaussian models where discrete and continuous variables co-exist, influence diagrams that are Bayesian networks augmented with decision variables and utility functions, limited-memory influence diagrams that allow the knowledge engineer to reduce model complexity through assumptions about limited memory of past events, object-oriented models that allow the knowledge engineer to construct hierarchical models consisting of reusable submodels, and dynamic Bayesian networks that provide a framework for modeling phenomena evolving over time.

In Chapter 5, we explain the principles underlying inference in these different kinds of probabilistic networks.

In Chapter 6, we discuss the art of constructing a probabilistic network, and the characteristics of problem domains that can be successfully modeled by probabilistic networks. The different phases of model construction is discussed, including design (how to identify the right set variables, how to elicit the structure of a probabilistic network, and the how to verify a network structure), implementation (elicitation of probability and utility parameters), test, and analysis (i.e., troubleshooting the model).

In Chapter 7, we present a large number of techniques and tricks for solving commonly occurring modeling problems in probabilistic networks. The set of techniques and tricks include various structure related techniques (parent divorcing, temporal transformation of causal relations, modeling of structural and functional uncertainty, modeling of undirected dependence relations and

bidirectional relations), probability distribution related techniques (modeling of measurement error, (different) expert opinions, node absorption, value set by intervention, and independence of causal influence), and decision related techniques (modeling of test decisions, missing informational links, missing observations, hypothesis of highest probability, and constraints on decisions).

In Chapter 8, we describe how probabilistic networks can be constructed automatically from a database of cases or from a combination of data and problem domain expertise. The underlying theory of structure learning is explained and different constraint-based learning algorithms are presented. The expectation-maximization (EM) algorithm is described for learning the values of probability parameters from data as well as from data and problem domain expertise (penalized EM). Finally, we describe how the values of the probability parameters of a probabilistic network can be learned sequentially (adaptation).

In Chapter 9, we describe a method for performing conflict analysis in a probabilistic network, which aims at detecting pieces of evidence that might be in conflict with one another (i.e., pointing in different directions with respect to output from the network) or in conflict with the network model. Also the topics of tracing and resolution of conflicts are discussed.

In Chapter 10, we describe how to analyze the sensitivity of the output of a probabilistic network (e.g., diagnosis, classification, etc.) to changes in the values of observed variables (evidence) as well as probability parameters.

Finally, in Chapter 11, we describe methods for performing value-of-information analyses in Bayesian networks as well as influence diagrams.

Aalborg,  
September 2007

*Uffe B. Kjærulff*  
*Anders L. Madsen*

---

# Contents

---

## Part I Fundamentals

---

<b>1</b>	<b>Introduction</b>	3
1.1	Expert Systems	3
1.1.1	Representation of Uncertainty	4
1.1.2	Normative Expert Systems	5
1.2	Rule-Based Systems	5
1.2.1	Causality	6
1.2.2	Uncertainty in Rule-Based Systems	7
1.2.3	Explaining Away	7
1.3	Bayesian Networks	8
1.3.1	Inference in Bayesian Networks	9
1.3.2	Construction of Bayesian Networks	10
1.3.3	An Example	10
1.4	Bayesian Decision Problems	13
1.5	When to Use Probabilistic Nets	14
1.6	Concluding Remarks	15
<b>2</b>	<b>Networks</b>	17
2.1	Graphs	18
2.2	Graphical Models	20
2.2.1	Variables	20
2.2.2	Vertices vs. Variables	21
2.2.3	Taxonomy of Vertices/Variables	22
2.2.4	Vertex Symbols	23
2.2.5	Summary of Notation	23
2.3	Evidence	23
2.4	Causality	24
2.5	Flow of Information in Causal Networks	25
2.5.1	Serial Connections	26
2.5.2	Diverging Connections	28

2.5.3	Converging Connections	29
2.5.4	The Importance of Correct Modeling of Causality	30
2.6	Two Equivalent Irrelevance Criteria	31
2.6.1	d-Separation Criterion	32
2.6.2	Directed Global Markov Criterion	33
2.7	Summary	35
<b>3</b>	<b>Probabilities</b>	<b>37</b>
3.1	Basics	38
3.1.1	Events	38
3.1.2	Conditional Probability	38
3.1.3	Axioms	39
3.2	Probability Distributions for Variables	40
3.2.1	Rule of Total Probability	41
3.2.2	Graphical Representation	43
3.3	Probability Potentials	44
3.3.1	Normalization	44
3.3.2	Evidence Potentials	45
3.3.3	Potential Calculus	46
3.3.4	Barren Variables	49
3.4	Fundamental Rule and Bayes' Rule	50
3.4.1	Interpretation of Bayes' Rule	51
3.5	Bayes' Factor	53
3.6	Independence	54
3.6.1	Independence and DAGs	56
3.7	Chain Rule	58
3.8	Summary	60
<b>4</b>	<b>Probabilistic Networks</b>	<b>63</b>
4.1	Reasoning Under Uncertainty	64
4.1.1	Discrete Bayesian Networks	65
4.1.2	Conditional Linear Gaussian Bayesian Networks	70
4.2	Decision Making Under Uncertainty	74
4.2.1	Discrete Influence Diagrams	75
4.2.2	Conditional LQG Influence Diagrams	85
4.2.3	Limited Memory Influence Diagrams	89
4.3	Object-Oriented Probabilistic Networks	91
4.3.1	Chain Rule	96
4.3.2	Unfolded OOPNs	96
4.3.3	Instance Trees	97
4.3.4	Inheritance	98
4.4	Dynamic Models	98
4.5	Summary	102

<b>5</b>	<b>Solving Probabilistic Networks</b>	107
5.1	Probabilistic Inference	108
5.1.1	Inference in Discrete Bayesian Networks	108
5.1.2	Inference in CLG Bayesian Networks	121
5.2	Solving Decision Models	124
5.2.1	Solving Discrete Influence Diagrams	124
5.2.2	Solving CLQG Influence Diagrams	129
5.2.3	Relevance Reasoning	130
5.2.4	Solving LIMIDs	133
5.3	Solving OOPNs	136
5.4	Summary	137

---

## Part II Model Construction

---

<b>6</b>	<b>Eliciting the Model</b>	143
6.1	When to Use Probabilistic Networks	144
6.1.1	Characteristics of Probabilistic Networks	145
6.1.2	Some Criteria for Using Probabilistic Networks	145
6.2	Identifying the Variables of a Model	147
6.2.1	Well-Defined Variables	147
6.2.2	Types of Variables	150
6.3	Eliciting the Structure	152
6.3.1	A Basic Approach	152
6.3.2	Idioms	154
6.4	Model Verification	159
6.5	Eliciting the Numbers	163
6.5.1	Eliciting Subjective Conditional Probabilities	163
6.5.2	Eliciting Subjective Utilities	166
6.5.3	Specifying CPTs and UTs Through Expressions	166
6.6	Concluding Remarks	170
6.7	Summary	172
<b>7</b>	<b>Modeling Techniques</b>	177
7.1	Structure Related Techniques	177
7.1.1	Parent Divorcing	178
7.1.2	Temporal Transformation	182
7.1.3	Structural and Functional Uncertainty	184
7.1.4	Undirected Dependence Relations	188
7.1.5	Bidirectional Relations	191
7.1.6	Naive Bayes Model	193
7.2	Probability Distribution Related Techniques	196
7.2.1	Measurement Uncertainty	196
7.2.2	Expert Opinions	199
7.2.3	Node Absorption	201

7.2.4	Set Value by Intervention . . . . .	202
7.2.5	Independence of Causal Influence . . . . .	205
7.2.6	Mixture of Gaussian Distributions . . . . .	210
7.3	Decision Related Techniques . . . . .	212
7.3.1	Test Decisions . . . . .	212
7.3.2	Missing Informational Links . . . . .	216
7.3.3	Missing Observations . . . . .	218
7.3.4	Hypothesis of Highest Probability . . . . .	220
7.3.5	Constraints on Decisions . . . . .	223
7.4	Summary . . . . .	225
<b>8</b>	<b>Data-Driven Modeling . . . . .</b>	<b>227</b>
8.1	The Task and Basic Assumptions . . . . .	228
8.2	Structure Learning From Data . . . . .	229
8.2.1	Basic Assumptions . . . . .	230
8.2.2	Equivalent Models . . . . .	231
8.2.3	Statistical Hypothesis Tests . . . . .	232
8.2.4	Structure Constraints . . . . .	235
8.2.5	PC Algorithm . . . . .	235
8.2.6	PC* Algorithm . . . . .	241
8.2.7	NPC Algorithm . . . . .	241
8.3	Batch Parameter Learning From Data . . . . .	246
8.3.1	Expectation-Maximization Algorithm . . . . .	247
8.3.2	Penalized EM Algorithm . . . . .	249
8.4	Sequential Parameter Learning . . . . .	252
8.5	Summary . . . . .	254

---

## Part III Model Analysis

---

<b>9</b>	<b>Conflict Analysis . . . . .</b>	<b>261</b>
9.1	Evidence Driven Conflict Analysis . . . . .	262
9.1.1	Conflict Measure . . . . .	262
9.1.2	Tracing Conflicts . . . . .	264
9.1.3	Conflict Resolution . . . . .	265
9.2	Hypothesis Driven Conflict Analysis . . . . .	267
9.2.1	Cost-of-Omission Measure . . . . .	267
9.2.2	Evidence with Conflict Impact . . . . .	267
9.3	Summary . . . . .	269
<b>10</b>	<b>Sensitivity Analysis . . . . .</b>	<b>273</b>
10.1	Evidence Sensitivity Analysis . . . . .	274
10.1.1	Distance and Cost-of-Omission Measures . . . . .	275
10.1.2	Identify Minimum and Maximum Beliefs . . . . .	276
10.1.3	Impact of Evidence Subsets . . . . .	277

10.1.4 Discrimination of Competing Hypotheses . . . . .	278
10.1.5 What-If Analysis . . . . .	279
10.1.6 Impact of Findings . . . . .	280
10.2 Parameter Sensitivity Analysis . . . . .	281
10.2.1 Sensitivity Function . . . . .	282
10.2.2 Sensitivity Value . . . . .	285
10.2.3 Admissible Deviation . . . . .	286
10.3 Summary . . . . .	287
<b>11 Value of Information Analysis . . . . .</b>	<b>291</b>
11.1 VOI Analysis in Bayesian Networks . . . . .	292
11.1.1 Entropy and Mutual Information . . . . .	292
11.1.2 Hypothesis Driven Value of Information Analysis . . . . .	293
11.2 VOI Analysis in Influence Diagrams . . . . .	297
11.3 Summary . . . . .	300
<b>References . . . . .</b>	<b>305</b>
<b>List of Symbols . . . . .</b>	<b>311</b>
<b>Index . . . . .</b>	<b>313</b>



## Part I

---

### Fundamentals

# Introduction

The desire to have computers perform intellectually challenging tasks has existed ever since the invention of the general-purpose computer that could be programmed to execute an arbitrary set of manipulations on numbers and symbols. Solving an intellectually challenging task can be characterized as a process of deriving conclusions (new pieces of knowledge) by manipulating a (large) body of knowledge, typically including definitions of entities (objects, concepts, events, phenomena, etc.), relations among them, and observations of states (values) of some of the entities.

As a prototypical example of a decision problem, imagine a physician who is consulted by a patient complaining about stomach pain. The physician then conducts an interview of the patient and possibly makes some investigations to localize the origin of the pain, to find other symptoms of the disorder, etc. Based on her knowledge about pathophysiological cause-effect mechanisms involving stomach pain as well as on the information revealed from the patient's medical records, from the interview, from the symptoms observed, etc., the physician makes a diagnosis and a treatment plan.

By formulating the physician's knowledge in an appropriate formal (computer) language for which there exist methods for making inferences to manipulate pieces of knowledge formulated in this language, the reasoning conducted by the physician can be automated and carried out by a computer. Probabilistic networks is an example of such a language that has gained a lot of popularity over the last couple of decades.

This chapter provides brief accounts on the context of probabilistic networks, what they are, and when to use them.

## 1.1 Expert Systems

A system that is able to perform tasks that are supposed to be intellectually demanding is often said to exhibit artificial intelligence (AI) or to be an expert system if the system's problem solving ability is restricted to a particular area

of expertise. Many definitions of artificial intelligence have been proposed. In this book, we shall consider techniques that enable us to construct devices and services that are able to

- perform reasoning and decision making under uncertainty,
- acquire knowledge from data/experience, and
- solve problems efficiently and respond to new situations.

We shall refrain from discussing whether or not this makes the devices or services exhibit AI, and leave this decision to the reader.

In any case, a probabilistic network is always constructed to solve a particular problem within a given problem domain (area of expertise). Therefore, the label “expert system” can often be attached to systems that perform reasoning and decision making by means of probabilistic networks.

The motivation for constructing an expert system is typically to automate some recurring task involving reasoning and decision making under uncertainty, possibly involving extraction of information/knowledge from data.

Several other expert system paradigms have been suggested. This book is not intended to provide accounts on such competing paradigms, but for the sake of historical context of probabilistic networks, we shall briefly mention some of the important and well-known alternatives to probabilistic networks.

### 1.1.1 Representation of Uncertainty

Randomness and uncertain judgment is inherent in most real-world decision problems. We therefore need a method (paradigm) that supports representation of quantitative measures of uncertain statements and a method for combining the measures such that reasoning and decision making under uncertainty can be automated.

Probability theory is the prevailing method for dealing with uncertainty, and it is the one in focus in this book. However, other methods have been proposed, as some researchers find probability theory inappropriate for presenting some forms of quantitative uncertainty. Probability theory deals with uncertainty of well-defined occurrences; i.e., the source of ambiguity is occurrence. Situations involving ambiguously and/or vaguely *defined* occurrences might be better represented by other methods. Let us very briefly mention the two most prominent alternative methods for dealing with uncertainty. Readers interested in more detailed accounts are referred to the literature.

Dempster and Shafer (Dempster 1968, Shafer 1976) developed belief theory to be able to assign measures of uncertainty to sets of events without necessarily having to assign or assess uncertainty for single events. For example, if you receive a message that your golf partner is free for a match of golf “next Sunday”, you might be willing to assign a measure of uncertainty to the pair of (mutually exclusive) events that you and your partner will be playing this Sunday or Sunday next week, but unwilling to assign measures to the two

individual possibilities. Rather than focusing on events, belief theory focuses on evidence (on sets of events).<sup>1</sup>

Fuzzy methods (Zadeh 1965, Zadeh & Kacprzyk 1992) address situations where the ambiguity lies in the nature of events rather than in their occurrence. Typical examples of ambiguous concepts include everyday concepts like beauty, intelligence, size, speed, etc. For example, both the statement “Paul is tall” ( $S$ ) and the statement “Paul is not tall” ( $\neg S$ ) might be plausible, and we therefore wish to assign some degree of plausibility to  $S \wedge \neg S$ , which is in contrast with ordinary logic where  $S \wedge \neg S$  is always false. Expert systems based on fuzzy logic have achieved some popularity, maybe especially so in applications involving control loops (fuzzy control).

### 1.1.2 Normative Expert Systems

The objective in some early attempts to construct expert systems was to create a model of the decision making performed by some (human) expert and let a system containing such a model perform tasks that previously needed human expertise. Today, a more realistic approach is normally taken where a model of the problem domain is created rather than a model of the expert such that systems containing such a model support experts in performing their tasks rather than substituting them.

Systems containing models of problem domains that use classical probability calculus and decision theory as their basis for reasoning and decision making under uncertainty are often referred to as *normative expert systems*, as their behavior is governed by a set of fundamental rules (or axioms).

In some sense, Bayesian networks can be seen as an extension of one of the earliest methods for knowledge representation and manipulation, namely logical rules. Let us therefore dwell a little on rule-based systems.

## 1.2 Rule-Based Systems

One of the earliest methods for knowledge representation and manipulation was logical rules of the form

$$R_1: \text{if } s_1 \text{ then } s_2,$$

where statement  $s_2$  (the consequence) can be concluded with certainty whenever statement  $s_1$  (the condition) is observed to hold. If another rule states that

$$R_2: \text{if } s_2 \text{ then } s_3,$$

then  $s_3$  can be concluded through *forward chaining* involving rules  $R_1$  and  $R_2$  once  $s_1$  is known to hold.

---

<sup>1</sup> Adapted from example by Bender (1996).

Notice that such rules are asymmetric in the sense that the condition and consequence statements are not interchangeable; observing the consequence statement does not allow us to conclude that the condition statement holds.

### 1.2.1 Causality

Assume that the occurrence of some event  $c$  is known to cause the effect  $e$  and that the relationship between  $c$  and  $e$  is known to be deterministic (logical). Then, obviously, observing  $c$  we can conclude  $e$ . Observing  $e$ , on the other hand, does not make us able to conclude  $c$ , unless  $c$  is known to be the only cause of  $e$ . Thus, in formulating the causal relationship between  $c$  and  $e$  as a rule we would obviously want to formulate it as “if  $c$  then  $e$ ” rather than “if  $e$  then  $c$ ”.

From this insight we conclude that rules like  $R_1$  and  $R_2$  express causal relationships, where  $s_1$ , say, plays the role of the cause and  $s_2$  the role of the effect, the only possible exception being if  $s_1$ , as an effect, only can be caused by  $s_2$ .

A rule-based system, like any other knowledge representation scheme, represents a certain part of the world (the problem domain) only up to some precision. This implies that certain (causal) mechanisms might be ignored as being unimportant for the precision (or level of detail) at which conclusions need to be drawn. For example, in a medical expert system, a disorder causing some symptom,  $s$ , might be ignored if it only appears in, say, less than one out of a million cases. If ignoring such a rare explanation for  $s$  leaves only one possible cause (disorder), say  $d$ , for the symptom, it might at a first consideration seem reasonable to state a rule like “if  $s$  then  $d$ ”.

Violating the “causal direction” in formulating rules is, however, not advisable. For example, in a medical expert system consider the causal chain

$$\text{smoking} \rightarrow \text{bronchitis} \rightarrow \text{dyspnoea},$$

denoting the concatenation of rules

$$R_3: \text{if smoking then bronchitis},$$

and

$$R_4: \text{if bronchitis then dyspnoea},$$

Here **bronchitis** is a disorder, **dyspnoea** (a medical term for shortness of breath) a symptom of **bronchitis**, and **smoking** a cause of **bronchitis**; sometimes referred to as a piece of background information. Assume that instead of  $R_4$  we formulated the rule

$$R'_4: \text{if dyspnoea then bronchitis},$$

which would make **smoking** and **dyspnoea** be competing explanations for **bronchitis**. Then upon observing that the patient smokes we would be able

to conclude only that the patient might suffer from bronchitis, but would not be able to conclude anything about the patient's breathing characteristics. In effect, rules  $R_3$  and  $R'_4$  collectively express independence between **smoking** and **dyspnoea**, which is obviously wrong.

### 1.2.2 Uncertainty in Rule-Based Systems

As clearly demonstrated by rules  $R_3$  and  $R_4$ , crisp logic is inappropriate for representing the nature of the causal relations among **smoking**, **bronchitis**, and **dyspnoea**. Only a certain proportion of the smoking patients entering a chest clinic suffer from bronchitis. Similarly, dyspnoea appears as a symptom only for some of the patients suffering from bronchitis. In terms of having uncertainty associated with the (cause–effect) rules, these examples are by no means exceptional. The vast majority of cause–effect mechanisms of interest in our attempts to model parts of the world in expert (or AI) systems are uncertain.

In order to make up for this fact, a method for rule-based systems with uncertainty was developed in the 1970s by the team behind the medical expert system MYCIN (Shortliffe & Buchanan 1975). Associated with each rule in MYCIN is a numerical value in the interval  $[-1, +1]$ , called a *certainty factor* (CF). This factor indicates the strength of the conclusion of the rule whenever its condition is satisfied. In particular, given the evidence available,

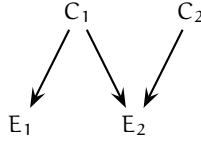
$$CF = \begin{cases} +1 & \text{when the conclusion is certainly true,} \\ -1 & \text{when the conclusion is certainly false,} \\ 0 & \text{when no information about the conclusion can be derived.} \end{cases}$$

Certainty factors are, however, nothing but an ad hoc device for dealing with uncertainty. Heckerman (1986) proved that certainty factors cannot be defined consistently if the domains of the variables have more than two elements. More precisely, certain factors can be proved to be consistent only for binary variables, where the rules induce a singly connected tree in which there is exactly one variable with no parents.<sup>2</sup>

### 1.2.3 Explaining Away

Consider the small rule system depicted in Figure 1.1, where  $C_1$  can cause  $E_1$  and  $E_2$ , and  $C_2$  can cause  $E_2$ . The CF method provides a formula for combining evidence from  $E_1$  and  $E_2$  and applying it to  $C_1$ . Unfortunately, however, the CF method provides no mechanism for applying  $E_1$  to  $C_2$ , which

<sup>2</sup> The variables in the condition of a rule are often referred to as the “parents” of the consequence variable, which is often referred to as the “child” variable. For example, variables **temperature** and **humidity** in rule “if **temperature** = **high** and **humidity** = **high** then **comfort** = **low**” are parents of **comfort**. A parent–child relation is depicted by two nodes in a graph (or tree) interconnected by a directed link from the parent to the child.



**Fig. 1.1.** Graphical representation of rules “if  $C_1$  then  $E_1$ ” and “if  $C_1$  and  $C_2$  then  $E_2$ ”.

is needed to implement the “explaining-away” mechanism, where evidence on  $E_1$  makes  $C_1$  more probable, in turn making the competing explanation  $C_2$  for  $E_2$  less probable.

### 1.3 Bayesian Networks

Having realized that rule-based systems with certainty factors have serious limitations as a method for knowledge representation and reasoning under uncertainty, researchers turned their attention towards a probabilistic interpretation of certainty factors, leading to the definition of Bayesian networks (Kim & Pearl 1983, Pearl 1988). A Bayesian network can be described briefly as an acyclic directed graph (DAG) which defines a factorization of a joint probability distribution over the variables that are represented by the nodes of the DAG, where the factorization is given by the directed links of the DAG. More precisely, for a DAG,  $\mathcal{G} = (\mathbf{V}, \mathbf{E})$ , where  $\mathbf{V}$  denotes a set of nodes (or vertices) and  $\mathbf{E}$  a set of directed links (or edges) between pairs of the nodes, a joint probability distribution,  $P(\mathbf{X}_{\mathbf{V}})$ , over the set of (typically discrete) variables  $\mathbf{X}_{\mathbf{V}}$  indexed by  $\mathbf{V}$  can be factorized as

$$P(\mathbf{X}_{\mathbf{V}}) = \prod_{v \in \mathbf{V}} P(X_v | X_{\text{pa}(v)}), \quad (1.1)$$

where  $X_{\text{pa}(v)}$  denotes the (preferably small) set of parent variables of variable  $X_v$  for each node  $v \in \mathbf{V}$ . The factorization in Equation 1.1 expresses a set of independence assumptions, which are represented by the DAG in terms of pairs of nodes that are not directly connected to one another by a directed link. It is the existence of such independence assumptions and the small set of parents for each node that makes it possible to specify the conditional probabilities and to perform inference efficiently in a Bayesian network.

Each conditional probability distribution,  $P(X_v | X_{\text{pa}(v)})$ , represents a set of “rules”, where each “rule” (conditional probability) takes the form

$$R_5: \text{if } X_{\text{pa}(v)} = x_{\text{pa}(v)} \text{ then } X_v = x_v \text{ with probability } z,$$

where  $x_v$  and  $x_{\text{pa}(v)}$  denote, respectively, a value assigned to  $X_v$  and a vector of values assigned to the parent variables of  $X_v$ . For example, if one of five possible values can be assigned to  $X_v$  and it has four parents each of which

can be assigned one of three possible values, then  $P(X_v|X_{pa(v)})$  represents a collection of  $5 \times 3^4 = 405$  rules of the kind shown in rule  $R_5$ .

Actually, the notion of rules is only implicitly apparent in Bayesian networks. The explicit notion is that of conditional probability distributions,  $P(X_v|X_{pa(v)})$ , where, rather than as in rule  $R_5$ , each term is formulated as a conditional probability (parameter) of the form

$$P(X_v = x_v | X_{pa(v)} = x_{pa(v)}) = z$$

or even simpler as

$$P(x_v | x_{pa(v)}) = z.$$

### 1.3.1 Inference in Bayesian Networks

Contrary to rule-based systems with certainty factors, inference in Bayesian networks is always consistent and the ability to handle the explaining-away problem is embedded naturally in the way in which inference is performed in Bayesian networks. However, in general, it is an NP-hard task to solve the inference problem in Bayesian networks (Cooper 1990); even approximate inference is NP-hard (Dagum & Luby 1993). Fortunately, efficient inference algorithms have been developed such that inference in Bayesian networks can be done in fractions of a second even for large networks containing hundreds of variables (Lauritzen & Spiegelhalter 1988, Jensen, Lauritzen & Olesen 1990). Efficiency of inference, however, is highly dependent on the structure of the DAG, so networks with a relatively small number of variables sometimes resist exact inference, in which case approximate methods must be applied.

As Bayesian networks most often represent causal statements of the kind  $X \rightarrow Y$ , where  $X$  is a cause of  $Y$  and where  $Y$  often takes the role of an observable effect of  $X$ , which typically cannot be observed itself, we need to derive the posterior probability distribution  $P(X|Y = y)$  given the observation  $Y = y$  using the prior distribution  $P(X)$  and the conditional probability distribution  $P(Y|X)$  specified in the model. Reverend Thomas Bayes (1702–1761) provided the famous Bayes' rule for performing this calculation:

$$P(X|Y = y) = \frac{P(Y = y|X)P(X)}{P(Y = y)},$$

where  $P(Y = y) = \sum_x P(Y = y|X = x)P(X = x)$ . This rule (or theorem) plays a central role in statistical inference because the probability of a cause can be inferred when its effect has been observed. Olmsted (1983) and Shachter (1986) developed a method for inference in Bayesian networks, which involved multiple applications of Bayes' rule. Lauritzen & Spiegelhalter (1988) and Jensen et al. (1990) developed inference methods for Bayesian networks based on message passing in a tree structure (junction tree) derived from the structure of the Bayesian network. The latter approach is the prevailing inference method used in modern software packages for inference in probabilistic networks.



### 1.3.2 Construction of Bayesian Networks

As described above, a Bayesian network can be described in terms of a qualitative component, consisting of a DAG, and a quantitative component, consisting of a joint probability distribution that factorizes into a set of conditional probability distributions governed by the structure of the DAG.

The construction of a Bayesian network thus runs in two phases. First, given the problem at hand, one identifies the relevant variables and the (causal) relations among them. The resulting DAG specifies a set of dependence and independence assumptions that will be enforced on the joint probability distribution, which is next to be specified in terms of a set of conditional probability distributions,  $P(X_v | X_{\text{pa}(v)})$ , one for each “family”,  $\{v\} \cup \text{pa}(v)$ , of the DAG.

A Bayesian network can be constructed manually, (semi-)automatically from data, or through a combination of a manual and a data driven process, where partial knowledge about structure as well as parameters (i.e., conditional probabilities) blend with statistical information extracted from databases of cases (i.e., previous joint observations of values of the variables).

Manual construction of a Bayesian network can be a labor-intensive task, requiring a great deal of skill and creativity as well as close communication with problem domain experts. Extensive guidance on how to manually construct a probabilistic network is the core of this book. This includes methods and hints on how to elicit the network structure (with emphasis on the importance of maintaining a causal perspective), methods for eliciting and specifying the parameter values of the network, and numerous tricks that can be applied for solving prototypical modeling problems.

Once constructed (be it manually or automatically), the parameters of a Bayesian network may be continuously updated as new information arrives. Thus, a model for which rough guesses on the parameter values are provided initially will gradually improve itself as it gets presented with more and more cases.

### 1.3.3 An Example

As a simple example, let us consider a problem concerning reasoning about starting problems for a car. Assume for simplicity that we only consider two competing causes for starting problems, namely no fuel and dirty spark plugs. Also assume that, apart from starting problems, the only observation we can make is reading the fuel gauge. Now, if the car will not start and the fuel gauge reads “empty”, then we conclude that “no fuel” is probably is the cause of the problem, and we strongly reduce our suspicion that dirty spark plugs might be causing the problem.

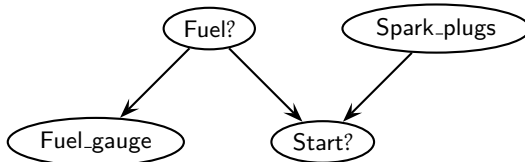
Let us see how to automate that reasoning process in a Bayesian network. First, we identify four variables and the possible values (states) that they may

Variable	Possible states
Start?	{no, yes}
Spark_plugs	{dirty, clean}
Fuel?	{no, yes}
Fuel_gauge	{empty, not_empty}

**Table 1.1.** The four variables and their possible states for the “car won’t start” problem.

attain (in this case no more than two states for each variable is necessary). The variables and their possible states are shown in Table 1.1.

Figure 1.2 shows the structure of the Bayesian network for this simple problem, where *Fuel?* and *Spark\_plugs* have causal influences on *Start?*, and *Fuel?* has a causal influence on *Fuel\_gauge*.



**Fig. 1.2.** Bayesian network for the “car won’t start” problem.

A (conditional) probability table needs to be specified for each variable. Assume that when knowing nothing about the states of the other variables we would expect that there is fuel on the car (i.e., *Fuel?* = *yes*) in 999 out of 1000 cases. Therefore, respecting the order of states in Table 1.1, we specify the probability distribution for *Fuel?* as

$$P(\text{Fuel?}) = (0.001, 0.999).$$

Similarly, expecting that the spark plugs are clean in 95 out of 100 cases, we specify

$$P(\text{Spark\_plugs}) = (0.05, 0.95).$$

For *Fuel\_gauge* we need to specify two conditional probability distributions, one for each possible state of *Fuel?*. For *Start?* we need to specify four conditional probability distributions, one for each combination of possible states of *Fuel?* and *Spark\_plugs*. These probability distributions appear in the conditional probability tables shown in Table 1.2 and Table 1.3, respectively, where we expect the fuel gauge to read empty with probability 0.995 if there is no fuel, the car to start with probability 0.99 when there is fuel on the car and the spark plugs are clean, etc. In Table 1.3, the probability of 0.01 for *Start?* = *no* when *Fuel?* = *yes* and *Spark\_plugs* = *clean* captures other causes not explicitly considered in our simple model.

From the probabilities specified we can compute that

Fuel_gauge	Fuel?	
	no	yes
empty	0.995	0.001
not_empty	0.005	0.999

**Table 1.2.** Conditional probability distributions for Fuel\_gauge given Fuel?,  $P(\text{Fuel\_gauge}|\text{Fuel?})$ .

Fuel?	Spark_plugs	Start?	
		no	yes
no	dirty	1	0
no	clean	1	0
yes	dirty	0.1	0.9
yes	clean	0.01	0.99

**Table 1.3.** Conditional probability distributions for Start? given Fuel? and Spark\_plugs,  $P(\text{Start?}|\text{Fuel?}, \text{Spark\_plugs})$ .

$$P(\text{Start?} = \text{no}) = 0.016,$$

i.e., we expect the car to start in 984 out of 1000 cases (or with probability 0.984). Now, if we fix the value of Start? to no, then, using Bayes' rule, we get

$$P(\text{Fuel?} = \text{no}|\text{Start?} = \text{no}) = 0.065$$

and

$$P(\text{Spark\_plugs} = \text{dirty}|\text{Start?} = \text{no}) = 0.326.$$

Thus, our best guess is that dirty spark plugs are causing the problem, although the probability of dirty spark plugs might not be high enough and the probability of “no fuel” not low enough to settle with the conclusion that dirty spark plugs are causing our problem. Making the observation that Fuel\_gauge = empty and repeating the computations, we find that

$$P(\text{Fuel?} = \text{no}|\text{Start?} = \text{no}, \text{Fuel\_gauge} = \text{empty}) = 0.986$$

and

$$P(\text{Spark\_plugs} = \text{dirty}|\text{Start?} = \text{no}, \text{Fuel\_gauge} = \text{empty}) = 0.054.$$

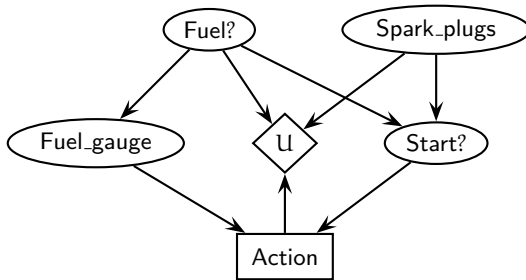
The observation Fuel\_gauge = empty thus makes us strongly believe that “no fuel” is the cause of the problem, as we see a dramatic increase in the probability of Fuel? = no and a (somewhat less dramatic) decrease in the probability of Spark\_plugs = dirty. The decrease in the probability of Spark\_plugs = dirty illustrates the explaining-away effect.

## 1.4 Bayesian Decision Problems

Most often, the outputs of interest of a Bayesian network are the posterior probabilities of the variables representing the problem that we wish to reason about (e.g., possible diagnoses). These probabilities are often combined with costs and benefits (utilities) of performing one or more actions to solve the problem. That is, from the posterior probabilities and the utilities we compute expected utilities for each possible decision option (e.g., different treatment alternatives). The decision option with the highest expected utility should then be selected. Based on a number of studies, Tversky & Kahneman (1981) have shown that people usually do *not* make decisions that maximize their expected utility.

A Bayesian network can be augmented with decision variables, representing decision options, and utility functions, representing preferences, that may depend on both random (or chance) variables and decision variables. Networks so augmented are called influence diagrams, and can be used to compute expected utilities for the various decision options given the observations (and decisions) made.

Assume that we wish to augment our Bayesian network in Figure 1.2 with a decision variable, say *Action*, with states {no\_action, add\_fuel, clean\_spark\_plugs} and a utility function, say *U*, that depends on the states of chance variables *Fuel?* and *Spark\_plugs* and on our decision variable. Figure 1.3 shows the structure of the augmented network, where the links from *Fuel\_gauge* and *Start?* to *Action* indicates that the states of *Fuel\_gauge* and *Start?* are known prior to making the decision on which action to perform. Table 1.4 shows our util-



**Fig. 1.3.** Influence diagram for the “car won’t start” problem.

ity function, where we assign a utility value of 1 to combinations of states of *Action*, *Fuel?*, and *Spark\_plugs* where the action is supposed to solve a problem; otherwise, we assign a value of 0 to the utility function.

With the evidence that *Start?* = no and *Fuel\_gauge* = empty we find that

$$EU(\text{Action}) = (0.009, 0.986, 0.054),$$

meaning that the expected utilities of decision options no\_action, add\_fuel, and clean\_spark\_plugs are 0.009, 0.986, and 0.054, respectively. Since  $EU(\text{add\_fuel})$

Fuel?	Spark_plugs	Action		
		no_action	add_fuel	clean_spark_plugs
no	dirty	0	1	1
no	clean	0	1	0
yes	dirty	0	0	1
yes	clean	1	0	0

**Table 1.4.** Utility function for the “car won’t start” decision problem.

is greater than both  $EU(\text{no\_action})$  and  $EU(\text{clean\_spark\_plugs})$ , we select decision option **add\_fuel**.

Note that, coincidentally,  $P(\text{Fuel?} = \text{no}) = EU(\text{add\_fuel})$  because of the way in which we have defined the utility function. In general, the domain of a utility function is the set of real numbers. If one defines the utility values on, say, a monetary scale, the expected utilities of one’s decision options can be interpreted directly as expected gains or losses on the chosen scale, say dollars.

## 1.5 When to Use Probabilistic Nets

There are many good reasons to choose probabilistic networks as the framework for solving inference and decision problems under uncertainty. As indicated above, these include (among others)

- coherent and mathematically sound handling of uncertainty,
- normative decision making,
- automated construction and adaptation of models based on data,
- intuitive and compact representation of cause–effect relations and (conditional) dependence and independence relations, and
- efficient solution of queries given evidence.

There are, however, some requirements to the nature of the problem that should be fulfilled for probabilistic networks to be an appropriate choice of method. Here, we shall just briefly mention some key requirements:

- The variables and events (i.e., possible values of the variables) of the problem domain must be well-defined.
- Knowledge should be available about the (causal) relations among the variables, the conditional probabilities quantifying the relations, and the utilities (preferences) associated with the various decision options.
- Uncertainty should be associated with at least some of the relations among the variables.
- The problem at hand should most probably contain an element of decision making involving a desire to maximize the expected utility of a decision.

Data are often available in the form of joint observations of a subset of the variables pertaining to the problem domain. Each set of joint observations pertains to a particular instance (case) of the problem domain. For example, data can be extracted from a database of customers, where a lot of features (e.g., gender, age, marital status, income, etc.) are recorded for each customer (case), and analyzed statistically to derive both structure and parameters of a probabilistic network. Such automatically generated models can reveal a lot of information about dependence and independence relations (and sometimes even causal mechanisms) among the variables, and thus provide new knowledge about the problem domain. Sometimes, however, the available data do not originate from variables with clearly understood semantics or the patterns of interactions among variables are complex. In such cases, a neural network model might be better suited, where the model consists of a function that attempts to match each input case with a desired output by iteratively tweaking a large number of coefficients (weights) until convergence (i.e., until the distance between the desired and the actual outputs is sufficiently small).

## 1.6 Concluding Remarks

In this brief introduction we have only touched superficially upon a few key characteristics of probabilistic networks. These and many more will be presented in much greater detail in the chapters to come.

Careful introductions to the fundamental concepts, theories, and methods underlying probabilistic networks as well as definitions of Bayesian networks, influence diagrams, and their variants are provided in the remaining chapters of Part I; i.e., Chapters 2–5. These chapters can be skipped if you already know enough about the basics of probabilistic networks and wish to dive directly into Part II covering topics on model elicitation, modeling techniques, and learning models from data, or Part III covering topics on model analysis.

## Networks

Probabilistic networks are graphical models of (causal) interactions among a set of variables, where the variables are represented as vertices (nodes) of a graph and the interactions (direct dependences) as directed edges (links or arcs) between the vertices. Any pair of unconnected vertices of such a graph indicates (conditional) independence between the variables represented by these vertices under particular circumstances that can easily be read from the graph. Hence, probabilistic networks capture a set of (conditional) dependence and independence properties associated with the variables represented in the network.

Graphs have proven themselves an intuitive language for representing such dependence and independence statements, and thus provide an excellent language for communicating and discussing dependence and independence relations among problem-domain variables. A large and important class of assumptions about dependence and independence relations expressed in factorized representations of joint probability distributions can be represented compactly in a class of graphs known as acyclic, directed graphs (DAGs).

Chain graphs are a generalization of DAGs, capable of representing a broader class of dependence and independence assumptions (Frydenberg 1989, Wermuth & Lauritzen 1990). The added expressive power comes, however, with the cost of a significant increase in the semantic complexity, making specification of joint probability factors much less intuitive. Thus, despite their expressive power, chain graph models have gained little popularity as practical models for decision support systems, and we shall therefore focus exclusively on models that factorize according to DAGs.

As indicated above, probabilistic networks is a class of probabilistic models that have gotten their name from the fact that the joint probability distributions represented by these models can be naturally described in graphical terms, where the vertices of a graph (or network) represent variables over which a joint probability distribution is defined and the presence and absence of edges represent dependence and independence properties among the variables.

Probabilistic networks can be seen as compact representations of “fuzzy” cause–effect rules that, contrary to ordinary (logical) rule-based systems, is capable of performing deductive and abductive reasoning as well as inter-causal reasoning. Deductive reasoning (sometimes referred to as *causal reasoning*) follows the direction of the causal links between variables of a model; e.g., knowing that a patient suffers from angina we can conclude (with high probability) the patient has fever and a sore throat. Abductive reasoning (sometimes referred to as *diagnostic reasoning*) goes against the direction of the causal links; e.g., observing that a patient has a sore throat provides supporting evidence for angina being the correct diagnosis.

The property, however, that sets inference in probabilistic networks apart from other automatic reasoning paradigms is its ability to make *inter-causal* reasoning: Getting evidence that supports solely a single hypothesis (or a subset of hypotheses) automatically leads to decreasing belief in the unsupported, competing hypotheses. This property is often referred to as the *explaining away* effect. For example, there is a large number of possible causes that a car will not start; one being lack of fuel. Observing that the fuel gauge indicates no fuel provides strong evidence that lack of fuel is the cause of the problem, while the beliefs in other possible causes decrease substantially (i.e., they are explained away by the observation). The ability of probabilistic networks to automatically perform such inter-causal inference is a key contribution to their reasoning power.

Often the graphical aspect of a probabilistic network is referred to as its *qualitative* aspect, and the probabilistic, numerical part as its *quantitative* aspect. This chapter is devoted to the qualitative aspect of probabilistic networks. In Section 2.1 we introduce some basic graph notation that will be used throughout the book. Section 2.2 discusses the notion of variables, which is the key entity of probabilistic networks. Another key concept is that of “evidence”, which we shall touch upon in Section 2.3. Maintaining a causal perspective in the model construction process can prove valuable, as mentioned briefly in Section 2.4. Sections 2.5 and 2.6 are devoted to an in-depth treatment on the principles and rules for flow of information in DAGs. We carefully explain the properties of the three basic types of connections in a DAG (i.e., serial, diverging, and converging connections) through examples, and show how these combine directly into the d-separation criterion and how they support inter-causal (explaining away) reasoning. We also present an alternative to the d-separation criterion known as the directed global Markov criterion, which in many cases proves to be a more efficient method for reading off dependence and independence statements of a DAG.

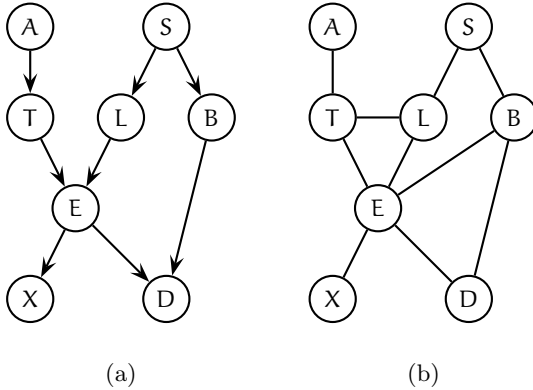
## 2.1 Graphs

A graph is a pair  $\mathcal{G} = (V, E)$ , where  $V$  is a finite set of distinct vertices and  $E \subseteq V \times V$  is a set of edges. An ordered pair  $(u, v) \in E$  denotes a *directed edge*



from vertex  $u$  to vertex  $v$ , and  $u$  is said to be a *parent* of  $v$  and  $v$  a *child* of  $u$ . The set of parents and children of a vertex  $v$  shall be denoted by  $\text{pa}(v)$  and  $\text{ch}(v)$ , respectively.

As we shall see later, depending on what they represent, vertices are displayed as labelled circles, ovals, or polygons, directed edges as arrows, and undirected edges as lines. Figure 2.1(a) shows a graph with 8 vertices and 8 edges (all directed), where, for example, the vertex labeled E has two parents labeled T and L. The labels of the vertices are referring to (i) the names of the vertices, (ii) the names of the variables represented by the vertices, or (iii) descriptive labels associated with the variables represented by the vertices.<sup>1</sup>



**Fig. 2.1.** (a) An acyclic, directed graph (DAG). (b) Moralized graph.

We often use the intuitive notation  $u \xrightarrow{\mathcal{G}} v$  to denote  $(u, v) \in E$  (or just  $u \rightarrow v$  if  $\mathcal{G}$  is understood). If  $(u, v) \in E$  and  $(v, u) \in E$ , the edge between  $u$  and  $v$  is an *undirected edge*, denoted by  $\{u, v\} \in E$  or  $u \xleftrightarrow{\mathcal{G}} v$  (or just  $u - v$ ). We shall use the notation  $u \sim v$  to denote that  $u \rightarrow v$ ,  $v \rightarrow u$ , or  $u - v$ . Vertices  $u$  and  $v$  are said to be *connected* in  $\mathcal{G}$  if  $u \sim v$ . If  $u \rightarrow v$  and  $w \rightarrow v$ , then these edges are said to meet *head-to-head* at  $v$ .

If  $E$  does not contain undirected edges, then  $\mathcal{G}$  is a *directed graph* and if  $E$  does not contain directed edges, then it is an *undirected graph*. As mentioned above, we shall not deal with mixed cases of both directed and undirected edges.

A *path*  $\langle v_1, \dots, v_n \rangle$  is a sequence of distinct vertices such that  $v_i \sim v_{i+1}$  for each  $i = 1, \dots, n-1$ ; the *length* of the path is  $n-1$ . The path is a *directed path* if  $v_i \rightarrow v_{i+1}$  for each  $i = 1, \dots, n-1$ ;  $v_i$  is then an *ancestor* of  $v_j$  and  $v_j$  a *descendant* of  $v_i$  for each  $j > i$ . The set of ancestors and descendants of  $v$  are denoted  $\text{an}(v)$  and  $\text{de}(v)$ , respectively. The set  $\text{nd}(v) = V \setminus \text{de}(v) \cup \{v\}$  are

<sup>1</sup> See Section 2.2 for the naming conventions used for vertices and variables.

called the *non-descendants* of  $v$ . The *ancestral set*  $An(u) \subseteq V$  of a set  $u \subseteq V$  of a graph  $\mathcal{G} = (V, E)$  is the set of vertices  $u \cup \bigcup_{u \in u} an(u)$ .

A path  $\langle v_1, \dots, v_n \rangle$  from  $v_1$  to  $v_n$  of an undirected graph,  $\mathcal{G} = (V, E)$ , is *blocked* by a set  $S \subseteq V$  if  $\{v_2, \dots, v_{n-1}\} \cap S \neq \emptyset$ . There is a similar concept for paths of acyclic, directed graphs (see below), but the definition is somewhat more complicated (see Proposition 2.4 on page 32).

A graph  $\mathcal{G} = (V, E)$  is *connected* if for any pair  $\{u, v\} \subseteq V$  there is a path  $\langle u, \dots, v \rangle$  in  $\mathcal{G}$ . A connected graph  $\mathcal{G} = (V, E)$  is a *tree* if for any pair  $\{u, v\} \subseteq V$  there is a unique path  $\langle u, \dots, v \rangle$  in  $\mathcal{G}$ .

A *cycle* is a path,  $\langle v_1, \dots, v_n \rangle$ , of length greater than two with the exception that  $v_1 = v_n$ ; a *directed cycle* is defined in the obvious way. A directed graph with no directed cycles is called an *acyclic, directed graph* or simply a *DAG*; see Figure 2.1(a) for an example. The undirected graph obtained from a DAG,  $\mathcal{G}$ , by replacing all its directed edges with undirected ones is known as the *skeleton* of  $\mathcal{G}$ .

Let  $\mathcal{G} = (V, E)$  be a DAG. The undirected graph,  $\mathcal{G}^m = (V, E^m)$ , where

$$E^m = \{\{u, v\} \mid u \text{ and } v \text{ are connected or have a common child in } \mathcal{G}\},$$

is called the *moral graph* of  $\mathcal{G}$ . That is,  $\mathcal{G}^m$  is obtained from  $\mathcal{G}$  by first adding undirected edges between pairs of unconnected vertices that share a common child, and then replacing all directed edges with undirected edges; see Figure 2.1(b) for an example.

## 2.2 Graphical Models

On a structural (or qualitative) level, probabilistic network models are graphs with the vertices representing variables and utility functions, and the edges representing different kinds of relations among the variables and utility functions.

### 2.2.1 Variables

A *chance variable* represents an exhaustive set of mutually exclusive events, referred to as the *domain* of the variable. These events are also often called states, levels, values, choices, options, etc. The domain of a variable can be discrete or continuous; discrete domains are always finite.

*Example 2.1.* Some sample variable domains can be

$\{\text{false}, \text{true}\}$   
 $\{\text{red}, \text{green}, \text{blue}\}$   
 $\{1, 3, 5, 7\}$   
 $\{-1.7, 0, 2.32, 5\}$   
 $\{< 0, 0 - 5, > 5\}$   
 $] - \infty; \infty[$   
 $[ ] - \infty; 0], ]0; 5], ]5; 10]]$

The penultimate domain in the above list represents a domain for a continuous variable; the remaining ones represent domains for discrete variables.

Throughout this book we shall use capital letters (possibly indexed) to denote variables or sets of variables and lower case letters (possibly indexed) to denote particular values of variables. Thus,  $X = x$  may either denote the fact that variable  $X$  attains the value  $x$  or the fact that the set of variables  $X = (X_1, \dots, X_n)$  attains the (vector) of values  $x = (x_1, \dots, x_n)$ . By  $\text{dom}(X) = (x_1, \dots, x_{\|X\|})$  we shall denote the domain of  $X$ , where  $\|X\| = |\text{dom}(X)|$  is the number of possible distinct values of  $X$ . If  $X = (X_1, \dots, X_n)$ , then  $\text{dom}(X)$  is the Cartesian product (or product space) over the domains of the variables in  $X$ . Formally,

$$\text{dom}(X) = \text{dom}(X_1) \times \dots \times \text{dom}(X_n),$$

and thus  $\|X\| = \prod_i \|X_i\|$ . For two (sets of) variables  $X$  and  $Y$  we shall write either  $\text{dom}(X \cup Y)$  or  $\text{dom}(X, Y)$  to denote  $\text{dom}(X) \times \text{dom}(Y)$ . If  $z \in \text{dom}(Z)$ , then by  $z_X$  we shall denote the projection of  $z$  to  $\text{dom}(X)$ , where  $X \cap Z \neq \emptyset$ .

*Example 2.2.* Assume that  $\text{dom}(X) = \{\text{true}, \text{false}\}$  and  $\text{dom}(Y) = \{\text{red}, \text{green}, \text{blue}\}$ . Then  $\text{dom}(X, Y) = \{(\text{true}, \text{red}), (\text{true}, \text{green}), (\text{true}, \text{blue}), (\text{false}, \text{red}), (\text{false}, \text{green}), (\text{false}, \text{blue})\}$ . For  $z = (\text{true}, \text{blue})$  we get  $z_X = \text{true}$  and  $z_Y = \text{blue}$ .

## Chance Variables and Decision Variables

There are basically two categories of variables, namely variables representing random events and variables representing choices under the control of some, typically human, agent. Consequently, the first category of variables is often referred to as *chance variables* (or *random variables*) and the second category as *decision variables*. Note that a random variable can depend functionally on other variables in which case it is sometimes referred to as a *deterministic (random) variable*. Sometimes it is important to distinguish between truly random variables and deterministic variables, but unless this distinction is important we shall treat them uniformly, and refer to them simply as “random variables”, or just “variables”.

The problem of identifying those entities of a domain that qualify as variables is not necessarily trivial. Also, identifying the “right” set of variables can be non-trivial. These questions, however, will not be further touched upon in this chapter, but will be discussed in detail in Chapter 6.

### 2.2.2 Vertices vs. Variables

The notions of variables and vertices (or nodes) are often used interchangeably for models containing no decision variables and utility functions (e.g., Bayesian networks). For models that contain decision variables and utility functions it is convenient to distinguish between variables and vertices, as a vertex does

not necessarily represent a variable. In this book we shall therefore maintain that distinction.

As indicated above, we shall use lower-case letters like  $u, v, w$  (or sometimes  $\alpha, \beta, \gamma$ , etc.) to denote vertices, and upper-case letters like  $U, V, W$  to denote sets of vertices. Vertex names will sometimes be used in the subscripts of variable names to identify the variables corresponding to vertices. For example, if  $v$  is a vertex representing a variable, then we denote that variable by  $X_v$ . If  $v$  represents a utility function, then  $X_{pa(v)}$  denotes the domain of the function, which is a set of chance and/or decision variables.

### 2.2.3 Taxonomy of Vertices/Variables

For convenience, we shall use the following terminology for classifying variables and/or vertices of probabilistic networks.

First, as discussed above, there are three main classes of vertices in probabilistic networks, namely vertices representing chance variables, vertices representing decision variables, and vertices representing utility functions. We define the *category* of a vertex to represent this dimension of the taxonomy.

Second, chance and decision variables as well as utility functions can be discrete or continuous. This dimension of the taxonomy will be characterized by the *kind* of the variable or vertex.

Finally, for discrete chance and decision variables, we shall distinguish between labeled, Boolean, numbered, and interval variables. For example, referring to Example 2.1 on page 20, the first domain is the domain of a Boolean variable, the second and the fifth are domains of labeled variables, the third and the fourth are domains of numbered variables, and the last is the domain of an interval variable. This dimension of the taxonomy is referred to by the *subtype* of discrete variables, and is useful for providing mathematical expressions of specifications of conditional probability tables and utility tables, as discussed in Chapter 6.







Table 2.1 summarizes the variable/vertex taxonomy.

Category	Kind	Subtype
Chance	Discrete	Labeled
Decision	Continuous	Boolean
Utility		Numbered
		Interval

**Table 2.1.** The taxonomy for variables/vertices. Note that the subtype dimension only applies for discrete chance and decision variables.

### 2.2.4 Vertex Symbols

Throughout this book we shall be using ovals to indicate discrete chance variables, rectangles to indicate discrete decision variables, and diamonds to indicate discrete utility functions. Continuous variables and utility functions are indicated with double borders. See Table 2.2 for an overview.

Category	Kind	Symbol
Chance	Discrete	
	Continuous	
Decision	Discrete	
	Continuous	
Utility	Discrete	
	Continuous	

**Table 2.2.** Vertex symbols.

### 2.2.5 Summary of Notation

Table 2.3 summarizes the notation used for vertices (upper part), variables (middle part), and utility functions (lower part).

## 2.3 Evidence

A key inference task with a probabilistic network is computation of posterior probabilities of the form  $P(x|\varepsilon)$ , where, in general,  $\varepsilon$  is *evidence* (i.e., information) received from external sources in the form of a *likelihood distribution* over the states of a set of variables,  $X$ , of the network; also often called an *evidence function* (or *potential*<sup>2</sup>) for  $X$ . An evidence function,  $\mathcal{E}_X$ , for a set,  $X$ , of variables is a function  $\mathcal{E}_X : \text{dom}(X) \rightarrow \mathbb{R}^+$ .

*Example 2.3.* If  $\text{dom}(X) = (x_1, x_2, x_3)$ , then  $\mathcal{E}_X = (1, 0, 0)$  is an evidence function indicating that  $X = x_1$  with certainty. If  $\mathcal{E}_X = (1, 2, 0)$ , then with certainty  $X \neq x_3$  and  $X = x_2$  is twice as likely as  $X = x_1$ .

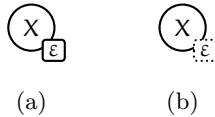
An evidence function that assigns a zero probability to all but one state is often said to provide *hard evidence*; otherwise, it is said to provide *soft evidence*. We shall often leave out the “hard” or “soft” qualifier, and simply talk about evidence if the distinction is immaterial. Hard evidence on a variable  $X$  is also often referred to as *instantiation* of  $X$  or we say that  $X$  has been *observed*.

<sup>2</sup> See Section 3.3 on page 44.

$S, U, V, W$	sets of vertices
$V$	set of vertices of a model
$V_\Delta$	the subset of $V$ that represent discrete variables
$V_\Gamma$	the subset of $V$ that represent continuous variables
$u, v, w, \dots$	vertices
$\alpha, \beta, \gamma, \dots$	vertices
<hr/>	
$X, Y_i, Z_k$	variables or sets of variables
$X_W$	subset of variables corresponding to set of vertices $W$
$\mathcal{X}$	the set of variables of a model; note that $\mathcal{X} = \mathcal{X}_V$
$\mathcal{X}_W$	subset of $\mathcal{X}$ , where $W \subseteq V$
$X_u, X_\alpha$	variables corresponding to vertices $u$ and $\alpha$ , respectively
$x, y_i, z_k$	configurations/states of (sets of) variables
$x_Y$	projection of configuration $x$ to $\text{dom}(Y)$ , $X \cap Y \neq \emptyset$
$\mathcal{X}_C$	the set of chance variables of a model
$\mathcal{X}_D$	the set of decision variables of a model
$\mathcal{X}_\Delta$	the subset of discrete variables of $\mathcal{X}$
$\mathcal{X}_\Gamma$	the subset of continuous variables of $\mathcal{X}$
<hr/>	
$\mathcal{U}$	the set of utility functions of a model
$V_u$	the subset of $V$ representing utility functions
$u(X)$	utility function $u \in \mathcal{U}$ with the set of variables $X$ as domain

**Table 2.3.** Notation used for vertices, variables, and utility functions.

We shall attach the label  $\boxed{\mathcal{E}}$  to vertices representing variables with hard evidence and the label  $\boxed{\mathcal{E}}$  to vertices representing variables with either soft or hard evidence. For example, hard evidence on variable  $X$  (like  $\mathcal{E}_X = (1, 0, 0)$  in Example 2.3 on the preceding page) is indicated as shown in Figure 2.2(a) and soft evidence (like  $\mathcal{E}_X = (1, 2, 0)$  in Example 2.3 on the previous page) is indicated as shown in Figure 2.2(b).

**Fig. 2.2.** (a) Hard evidence on  $X$ . (b) Soft (or hard) evidence on  $X$ .

## 2.4 Causality

Causality plays an important role in the process of constructing probabilistic network models. There are a number of reasons why proper modeling of causal relations is important or helpful, although, in a Bayesian network model, it is not strictly necessary to have the directed links of the model follow a causal interpretation. In models with explicit representation of decisions (influence

diagrams), the directed links must represent causal relations. We shall only briefly touch upon the issue of causality, and stress a few important points about causal modeling. The reader is referred to Pearl's work for an in-depth treatment of the subject (Pearl 2000).

A variable  $X$  is said to be a direct cause of  $Y$  if setting the value of  $X$  by force, the value of  $Y$  may change and there is no other variable  $Z$  that is a direct cause of  $Y$  such that  $X$  is a direct cause of  $Z$ ; see Pearl's work for details.

As an example, consider the variables **Flu** and **Fever**. Common sense tells us that flu is a cause of fever, not the other way around. This fact can be verified from the thought experiment of forcefully setting the states of **Flu** and **Fever**: Killing fever with an aspirin or by taking a cold shower will have no effect on the state of **Flu**, whereas eliminating a flu would make the body temperature go back to normal (assuming flu is the only effective cause of fever).

To correctly represent the dependence and independence relations that exist among a set of variables of a problem domain it is useful to have the causal relations among the variables represented in terms of directed links from causes to effects. That is, if  $X$  is a direct cause of  $Y$ , we should make sure to add a directed link from  $X$  to  $Y$ . If done the other way around (i.e.,  $Y \rightarrow X$ ), we may end up with a model that does not properly represent the dependence and independence relations of the problem domain. In subsequent sections, we shall see several examples of the importance of respecting the causal relations in this sense.

That said, however, one does not *have* to construct a model where the links can be interpreted as causal relations, it just makes the model much more intuitive, eases the process of getting the dependence and independence relations right, and significantly eases the process of eliciting the conditional probabilities of the model. In Section 2.5.4 on page 30, we shall briefly return to the issue of the importance of correctly modeling the causal relationships in probabilistic networks.

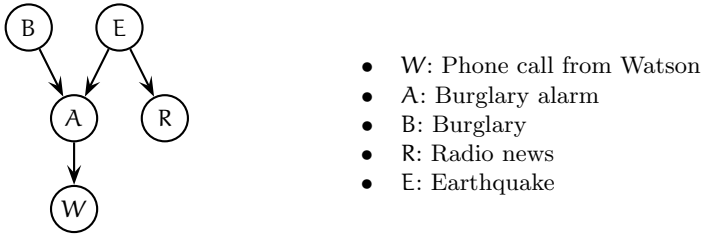
## 2.5 Flow of Information in Causal Networks

As mentioned above, the DAG of a probabilistic network model is a graphical representation of the dependence and independence properties of the joint probability distribution of the model. In this section we shall see how to read these properties from a DAG. In doing this, it is convenient to consider each possible basic kind of connection that can exist in a DAG.

To illustrate the different kinds of connections, consider the example in Figure 2.3 on the next page, which shows the structure of a probabilistic network for the following small fictitious example, where each variable has two possible states, *no* and *yes*.

*Example 2.4 (Burglary or Earthquake (Pearl 1988)).* Mr Holmes is working in his office when he receives a *phone call* from his neighbor Dr Watson, who tells

him that Holmes' *burglar alarm* has gone off. Convinced that a *burglar* has broken into his house, Holmes rushes to his car and heads for home. On his way, he listens to the radio, and in the *news* it is reported that there has been a small *earthquake* in the area. Knowing that earthquakes have a tendency to make burglar alarms go off, he returns to his work.



**Fig. 2.3.** Structure of a probabilistic network model for the “Burglary or Earthquake” story of Example 2.4 on the previous page.

Notice that all of the links in the network of Figure 2.3 are causal: Burglary or earthquake can cause the alarm to go off, earthquake can cause a report on earthquake in the radio news, and the alarm can cause Dr Watson to call Mr Holmes.

We see three different kinds of connections in the network of Figure 2.3:

- two *serial connections*  $B \rightarrow A \rightarrow W$  and  $E \rightarrow A \rightarrow W$ ,
- one *diverging connection*  $A \leftarrow E \rightarrow R$ , and
- one *converging connection*  $B \rightarrow A \leftarrow E$ .

In the following sub-sections we discuss each of these three possible kinds of connections in terms of their ability to transmit information given evidence and given no evidence on the middle variable, and we shall see that it is the converging connection that provides the ability of probabilistic networks to perform inter-causal reasoning (explaining away).

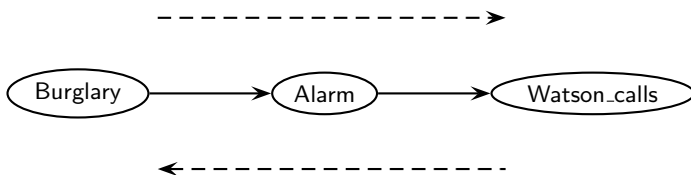
### 2.5.1 Serial Connections

Let us consider the serial connection (causal chain) depicted in Figure 2.4 on the facing page, referring to Example 2.4 on the previous page.

We need to consider two cases, namely with and without hard evidence (see Section 2.3 on page 23) on the middle variable (*Alarm*).

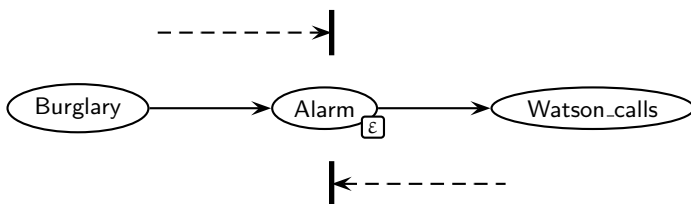
First, assume we do not have definite knowledge about the state of *Alarm*. Then evidence about *Burglary* will make us update our belief about the state of *Alarm*, which in turn will make us update our belief about the state of *Watson.calls*. The opposite is also true: If we receive information about the state of *Watson.calls*, that will influence our belief about the state of *Alarm*, which in turn will influence our belief about *Burglary*.





**Fig. 2.4.** Serial connection (causal chain) with no hard evidence on **Alarm**. Evidence on **Burglary** will affect our belief about the state of **Watson\_calls** and vice versa.

So, in conclusion, as long as we do not know the state of **Alarm** for sure, information about either **Burglary** or **Watson\_calls** will influence our belief on the state of the other variable. This is illustrated in Figure 2.4 by the two dashed arrows, signifying that evidence may be transmitted through a serial connection as long as we do not have definite knowledge about the state of the middle variable.



**Fig. 2.5.** Serial connection (causal chain) with hard evidence on **Alarm**. Evidence on **Burglary** will have no affect on our belief about the state of **Watson\_calls** and vice versa.

Next, assume we do have definite knowledge about the state of **Alarm** (see Figure 2.5). Now, given that we have hard evidence on **Alarm** any information about the state of **Burglary** will not make us change our belief about **Watson\_calls** (provided **Alarm** is the only cause of **Watson\_calls**; i.e., that the model is correct). Also, information about **Watson\_calls** will have no influence on our belief about **Burglary** when the state of **Alarm** is known for sure.

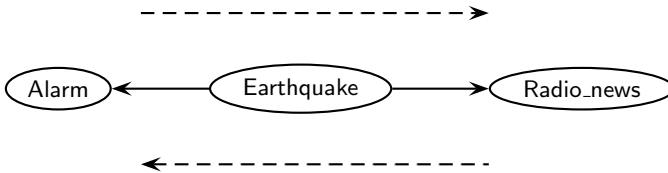
In conclusion, when the state of the middle variable of a serial connection is known for sure (i.e., we have hard evidence on it), then transmission of evidence between the other two variables cannot take place through this connection. This is illustrated in Figure 2.5 by the two dashed arrows ending at the observed variable, indicating that transmission of evidence is blocked.

The general rule for transmission of evidence in serial connections can thus be stated as follows:

**Proposition 2.1 (Serial connection).** *Information may be transmitted through a serial connection  $X \rightarrow Y \rightarrow Z$  unless the state of  $Y$  is known.*

### 2.5.2 Diverging Connections

Consider the diverging connection depicted in Figure 2.6, referring to Example 2.4 on page 25.

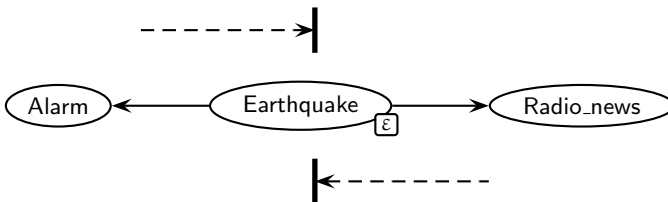


**Fig. 2.6.** Diverging connection with no evidence on **Earthquake**. Evidence on **Alarm** will affect our belief about the state of **Radio\_news** and vice versa.

Again, we consider the cases with and without hard evidence on the middle variable (**Earthquake**).

First, assume we do not know the state of **Earthquake** for sure. Then receiving information about **Alarm** will of course influence our belief about **Earthquake**, as earthquake is a possible explanation for alarm. The updated belief about the state of **Earthquake** will in turn make us update our belief about the state of **Radio\_news**. The opposite case (i.e., receiving information about **Radio\_news**) will, of course, lead to a similar conclusion. So, we get a result that is similar to the result for serial connections, namely that evidence can be transmitted through a diverging connection if we do not have definite knowledge about the state of the middle variable. This result is illustrated in Figure 2.6.

Next, assume the state of **Earthquake** is known for sure (i.e., we have received hard evidence on that variable). Now, if information is received about the state of either **Alarm** or **Radio\_news**, then this information is not going to change our belief about the state of **Earthquake**, and consequently we are not going to update our belief about the other, yet unobserved, variable. Again, this result is similar to the case for serial connections, and is illustrated in Figure 2.7.



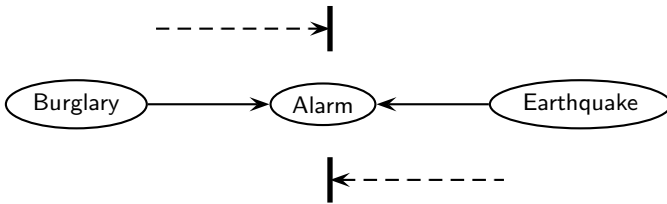
**Fig. 2.7.** Diverging connection with hard evidence on **Earthquake**. Evidence on **Alarm** will not affect our belief about the state of **Radio\_news** and vice versa.

The general rule for transmission of evidence in diverging connections can be stated as follows:

**Proposition 2.2 (Diverging connection).** *Information may be transmitted through a diverging connection  $X \leftarrow Y \rightarrow Z$  unless the state of  $Y$  is known.*

### 2.5.3 Converging Connections

Consider the converging connection depicted in Figure 2.8, referring to Example 2.4 on page 25.

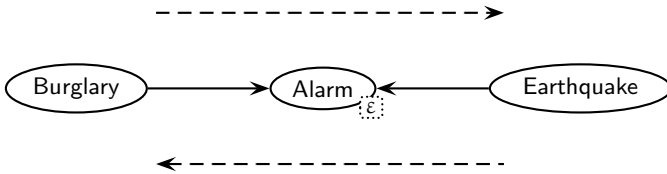


**Fig. 2.8.** Converging connection with no evidence on **Alarm** or any of its descendants. Information about **Burglary** will not affect our belief about the state of **Earthquake** and vice versa.

First, if no evidence is available about the state of **Alarm**, then information about the state of **Burglary** will not provide any derived information about the state of **Earthquake**. In other words, burglary is not an indicator of earthquake, and vice versa (again, of course, assuming correctness of the model). Thus, contrary to serial and diverging connections, a converging connection will not transmit information if no evidence is available for the middle variable. This fact is illustrated in Figure 2.8.

Second, if evidence is available on **Alarm**, then information about the state of **Burglary** will provide an explanation for the evidence that was received about the state of **Alarm**, and thus either confirm or disconfirm **Earthquake** as the cause of the evidence received for **Alarm**. The opposite, of course, also holds true. Again, contrary to serial and diverging connections, converging connections allow transmission of information whenever evidence about the middle variable is available. This fact is illustrated in Figure 2.9 on the following page.

The rule illustrated in Figure 2.8 tells us that if nothing is known about a common effect of two (or more) causes, then the causes are independent; i.e., receiving information about one of them will have no impact on the belief about the other(s). However, as soon as some evidence is available on a common effect the causes become dependent. If, for example, Mr Holmes receives a phone call from Dr Watson, telling him that his burglar alarm has gone off, burglary and earthquake become competing explanations for this effect,



**Fig. 2.9.** Converging connection with (possibly soft) evidence on **Alarm** or any of its descendants. Information about **Burglary** will affect our belief about the state of **Earthquake** and vice versa.

and receiving information about the possible state of one of them obviously either confirms or disconfirms the other one as the cause of the (possible) alarm. Note that even if the information received from Dr Watson might not be totally reliable (amounting to receiving soft evidence on **Alarm**), **Burglary** and **Earthquake** still become dependent.

The general rule for transmission of evidence in converging connections can then be stated as:

**Proposition 2.3 (Converging connection).** *Information may only be transmitted through a converging connection  $X \rightarrow Y \leftarrow Z$  if evidence on  $Y$  or one of its descendants is available.*

### Inter-causal Inference (Explaining Away)

The property of converging connections,  $X \rightarrow Y \leftarrow Z$ , that information about the state of  $X$  ( $Z$ ) provides an explanation for an observed effect on  $Y$ , and hence confirms or disconfirms  $Z$  ( $X$ ) as the cause of the effect, is often referred to as the *explaining away* effect or as *inter-causal inference*. For example, getting a radio report on earthquake provides strong evidence that the earthquake is responsible for a burglar alarm, and hence explaining away a burglary as the cause of the alarm.

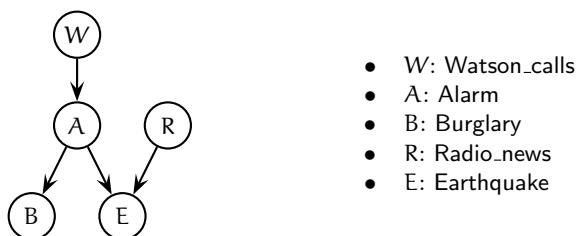
The ability to perform inter-causal inference is unique for graphical models, and is one of the key differences between automatic reasoning systems based on probabilistic networks and systems based on, for example, production rules. In a rule-based system we would need dedicated rules for taking care of inter-causal reasoning.

#### 2.5.4 The Importance of Correct Modeling of Causality

It is a common modeling mistake to let arrows point from effect to cause, leading to faulty statements of (conditional) dependence and independence and, consequently, faulty inference. For example, in the “Burglary or Earthquake” example on page 25 one might put a directed link from  $W$  (**Watson\_calls**) to  $A$  (**Alarm**) because the fact that Dr Watson makes a phone call to Mr Holmes

“points to” the fact that Mr Holmes’ alarm has gone off, etc. Experience shows that this kind of reasoning is common when people are building their first probabilistic networks, and is probably due to a mental flow-of-information model, where evidence acts as the “input” and the derived conclusions as the “output”.

Using this faulty modeling approach, the “Burglary or Earthquake” model in Figure 2.3 on page 26 would have all its links reversed (see Figure 2.10). Using Proposition 2.2 on page 29 on the model in Figure 2.10 we find that B and E are dependent when nothing is known about A, and, using Proposition 2.3 on the preceding page, we find that A and R are dependent whenever evidence about E is available. Neither of these conclusions are, of course, true, and will make the model make wrong inferences.



**Fig. 2.10.** Wrong model for the “Burglary or Earthquake” story of Example 2.4 on page 25, where the links are directed from effects to causes, leading to faulty statements of (conditional) dependence and independence.

Having the causal relations among domain variables be mapped to directed links  $X \rightarrow Y$ , where  $X$  is a cause of  $Y$ , is thus (at least) helpful, if not crucial, to having the model correctly represent the dependence and independence properties of the problem domain.

Another reason why respecting a causal modeling approach is important stems from the potential difficulties in specifying the conditional probability of  $X = x$  given that  $Y = y$  when  $Y \rightarrow X$  does not reflect a causal relationship. For example, it might be difficult for Mr Holmes to specify the probability that a burglar has broken into his house given that he knows the alarm has gone off, as the alarm might have gone off for other reasons. Thus, specifying the probability that the alarm goes off given its possible causes might be easier and more natural, providing a sort of complete description of a local phenomenon. We shall leave the discussion of this important issue for now and resume in Chapter 4 and Chapter 6.

## 2.6 Two Equivalent Irrelevance Criteria

Propositions 2.1–2.3 comprise the components needed to formulate a general rule for reading off the statements of relevance and irrelevance relations for

two (sets of) variables, possibly given a third variable (or set of variables). This general rule is known as the d-separation criterion and is due to Pearl (1988).

In Chapter 3 we show that for any joint probability distribution that factorizes according to a DAG,  $\mathcal{G}$ , (see Chapter 3 for a definition) independence statements involving variables  $X_u$  and  $X_v$  (again, see Chapter 3 for a definition) are equivalent to similar statements about d-separation of vertices  $u$  and  $v$  in  $\mathcal{G}$ .

Thus, the d-separation criterion may be used to answer queries of the kind “are  $X$  and  $Y$  independent given  $Z$ ” (in a probabilistic sense) or, more generally, queries of the kind “is information about  $X$  irrelevant for our belief about the state of  $Y$  given information about  $Z$ ”, where  $X$  and  $Y$  are individual variables and  $Z$  is either the empty set of variables or an individual variable.

The d-separation criterion may also be used with sets of variables, although this may be cumbersome. On the other hand, answering such queries is efficient using the directed global Markov criterion (Lauritzen, Dawid, Larsen & Leimer 1990b), which is a criterion that is equivalent to the d-separation criterion.

As statements of (conditional) d-separation/d-connection play a key role in probabilistic networks, some shorthand notation is convenient. We shall use the standard notation  $u \perp_{\mathcal{G}} v$  to denote that vertices  $u$  and  $v$  are d-separated in DAG  $\mathcal{G}$ , or simply  $u \perp v$  if  $\mathcal{G}$  is obvious from the context. By  $u \perp v | w$  we denote the statement that  $u$  and  $v$  are d-separated given (hard) evidence on  $w$ . By  $U \perp V$  we denote the fact that  $u \perp v$  for each  $u \in U$  and each  $v \in V$ . We shall use  $\not\perp$  to denote d-connection.

*Example 2.5 (Burglary or Earthquake, page 25).* Some of the d-separation/d-connection properties observed in the “Burglary or Earthquake” example are:

- (1) Burglary  $\perp$  Earthquake
- (2) Burglary  $\not\perp$  Earthquake | Alarm
- (3) Burglary  $\perp$  Radio\_report
- (4) Burglary  $\perp$  Watson\_calls | Alarm

Also, notice that d-separation and d-connection depends on the information available; i.e., it depends on what you know (and do not know). Also, note that, d-separation and d-connection relations are always symmetric; i.e.,  $u \perp v \equiv v \perp u$ .

### 2.6.1 d-Separation Criterion

Propositions 2.1–2.3 can be summarized into a rule known as *d-separation* (Pearl 1988):

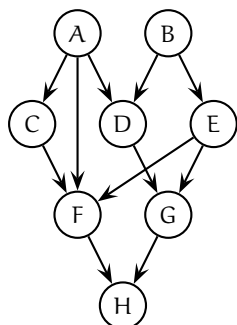
**Proposition 2.4 (d-Separation).** *A path  $\pi = \langle u, \dots, v \rangle$  in a DAG,  $\mathcal{G} = (V, E)$ , is said to be blocked by  $S \subseteq V$  if  $\pi$  contains a vertex  $w$  such that either*

- $w \in S$  and the edges of  $\pi$  do not meet head-to-head at  $w$ , or
- $w \notin S$ ,  $\text{de}(w) \cap S = \emptyset$ , and the edges of  $\pi$  meet head-to-head at  $w$ .

For three (not necessarily disjoint) subsets  $A, B, S$  of  $V$ ,  $A$  and  $B$  are said to be d-separated if all paths between  $A$  and  $B$  are blocked by  $S$ .

Proposition 2.4 on the facing page says, for example, that two vertices  $u$  and  $v$  are d-separated if for each path between  $u$  and  $v$  there is a vertex  $w$  such that the edges of the path meet head-to-head at  $w$ .

*Example 2.6 (d-Separation).* We may use Proposition 2.4 to determine if, for example, variables  $C$  and  $G$  are d-separated in the DAG in Figure 2.11; that is, are  $C$  and  $G$  independent when no evidence about any of the variables is available? First, we find that there is a diverging connection  $C \leftarrow A \rightarrow D$  allowing transmission of information from  $C$  to  $D$  via  $A$ . Second, there is a serial connection  $A \rightarrow D \rightarrow G$  allowing transmission of information from  $A$  to  $G$  via  $D$ . So, information can thus be transmitted from  $C$  to  $G$  via  $A$  and  $D$ , meaning that  $C$  and  $G$  are not d-separated (i.e., they are d-connected).



- (1)  $C$  and  $G$  are d-connected
- (2)  $C$  and  $E$  are d-separated
- (3)  $C$  and  $E$  are d-connected given evidence on  $G$
- (4)  $A$  and  $G$  are d-separated given evidence on  $D$  and  $E$
- (5)  $A$  and  $G$  are d-connected given evidence on  $D$

**Fig. 2.11.** Sample DAG with a few sample dependence (d-connected) and independence (d-separated) statements.

$C$  and  $E$ , on the other hand, are d-separated, since each path from  $C$  to  $E$  contains a converging connection, and since no evidence is available, each such connection will not allow transmission of information. Given evidence on one or more of the variables in the set  $\{D, F, G, H\}$ ,  $C$  and  $E$  will, however, become d-connected. For example, evidence on  $H$  will allow the converging connection  $D \rightarrow G \leftarrow E$  to transmit information from  $D$  to  $E$  via  $G$ , as  $H$  is a child of  $G$ . Then information may be transmitted from  $C$  to  $E$  via the diverging connection  $C \leftarrow A \rightarrow D$  and the converging connection  $D \rightarrow G \leftarrow E$ .

### 2.6.2 Directed Global Markov Criterion

The directed global Markov criterion (Lauritzen et al. 1990b) provides a criterion that is equivalent to that of the d-separation criterion, but which in

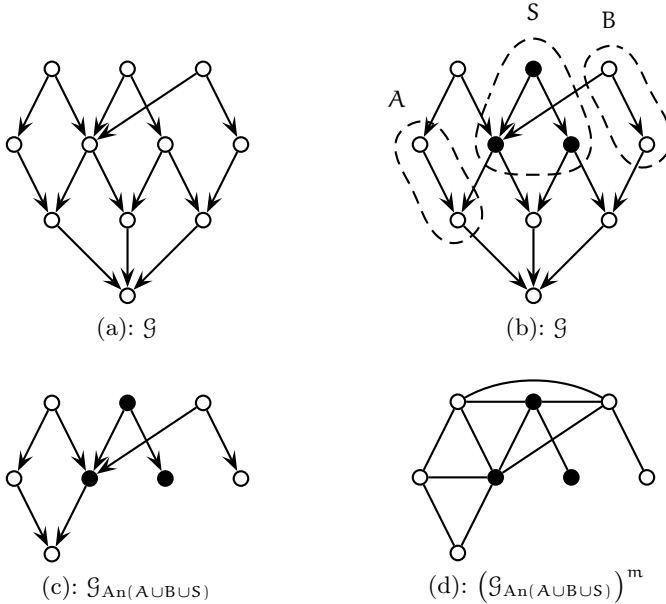
some cases may prove more efficient in terms of requiring less inspections of possible paths between the involved vertices of the graphs.

**Proposition 2.5 (Directed Global Markov Criterion).** *Let  $\mathcal{G} = (V, E)$  be a DAG and  $A, B, S$  be disjoint sets of  $V$ . Then each pair of vertices ( $\alpha \in A, \beta \in B$ ) are  $d$ -separated by  $S$  whenever each path from  $\alpha$  to  $\beta$  is blocked by vertices in  $S$  in the graph*

$$(\mathcal{G}_{\text{An}(A \cup B \cup S)})^m.$$

Although the criterion might look somewhat complicated at a first glance, it is actually quite easy to apply. The criterion says that  $A \perp_{\mathcal{G}} B | S$  if all paths from  $A$  to  $B$  passes at least one vertex in  $S$  in the moral graph of the sub-DAG induced by the ancestral set of  $A \cup B \cup S$ .

*Example 2.7 (Directed Global Markov Criterion).* Consider the DAG,  $\mathcal{G} = (V, E)$ , in Figure 2.12(a), and let the subsets  $A, B, S \subseteq V$  be given as shown in Figure 2.12(b). That is, we ask if  $A \perp_{\mathcal{G}} B | S$ . Using Proposition 2.5, we first



**Fig. 2.12.** (a) A DAG,  $\mathcal{G}$ . (b)  $\mathcal{G}$  with subsets  $A, B$ , and  $S$  indicated, where the variables in  $S$  are assumed to be observed. (c) The subgraph induced by the ancestral set of  $A \cup B \cup S$ . (d) The moral graph of the DAG of part (c).

remove each vertex not belonging to the ancestral set  $\text{An}(A \cup B \cup S)$ . This gives us the DAG in Figure 2.12(c). Second, we moralize the resulting sub-DAG, which gives us the undirected graph in Figure 2.12(d). Then, to answer the



query, we consult this graph to see if there is a path from a vertex in  $A$  to a vertex in  $B$  that do not contain a vertex in  $S$ . Since this is indeed the case, we conclude that  $A \not\perp_g B|S$ .

## 2.7 Summary

In this chapter we first defined some key concepts used to describe the qualitative part (i.e., the graphical structure) of probabilistic networks that are given by acyclic, directed graphs (DAGs). We defined the notion of the moral graph of a DAG, which plays an important role in understanding the independence properties represented by a DAG and in generating a junction tree for making inference in a probabilistic network (cf. Chapter 5).

We introduced the taxonomy of variables and vertices (the nodes of the DAG of a probabilistic network that represent the chance and decision variables and the utility functions of the network) and discussed the notions of product spaces over the domains of variables and projections down to smaller-dimensional spaces, which play a crucial role in inference processes (in Chapter 3 we shall see how the operation of projection is defined for probability functions). Also, the notion of evidence was briefly touched upon, including the distinction between hard and soft evidence.

To understand the notion of (conditional) independence in probabilistic networks, we discussed the three fundamental constructs (serial, diverging, and converging connections), in terms of which any path  $X \sim Y \sim Z$  of a DAG can be described. When the directed links of a DAG can be interpreted as causal links the three fundamental constructs have clear relevance properties, which can be described collectively by means of the d-separation criterion that can be used to determine if information about one set of variables is relevant to another set of variables, possibly given information about the states of a third set of variables (i.e., can information flow from the first set to the second set given the third set). An equivalent criterion (the directed, global Markov criterion), which uses the notion of moral graphs, was also presented.

In Chapter 3 we shall see that if a joint probability distribution factorizes according to the structure of a DAG, then the DAG is a graphical representation of the independence properties of the distribution. We briefly discussed the importance of having the directed edges of a DAG of a probabilistic network represent causal relations (i.e., the directed links should point from cause to effect). Otherwise, problems might arise both in terms of getting the right (conditional) independence properties of the network and in terms of ease of specification of the conditional probabilities (parameters) of the network. This important issue will be further discussed in Chapter 4 and Chapter 6.

## Exercises

**Exercise 2.1.** For the discrete variables  $X$ ,  $Y$ , and  $Z$  assume that  $\text{dom}(X) = \{0, 1\}$ ,  $\text{dom}(Y) = \{\text{good}, \text{bad}\}$ , and  $\text{dom}(Z) = \{\text{low}, \text{average}, \text{high}\}$ .

- (a) What is  $||(\mathbf{X}, \mathbf{Y}, \mathbf{Z})||$ ?
- (b) Specify  $\text{dom}(X, Y = \text{good}, Z)$ .
- (c) Let  $w = (1, \text{good}, \text{high})$ . Specify  $w_{\{X, Z\}}$  and  $w_Y$ .
- (d) Specify evidence functions for  $Z$  that indicate
  - (i)  $Z = \text{low}$  with certainty,
  - (ii)  $Z \neq \text{low}$  and  $Z = \text{high}$  is three times as likely as  $Z \neq \text{average}$ .

**Exercise 2.2.** Direct the links below such that the parent nodes represent the causes and the child nodes represent the effects.

- (a) Flu — Fever
- (b) State\_of\_battery — Age\_of\_battery
- (c) Living\_standard — Education
- (d) Age — Number\_of\_children
- (e) Occupation — Education
- (f) Fake\_die — Number\_of\_6s

**Exercise 2.3.** Consider the DAG in Figure 2.11 on page 33. Use the d-separation criterion to test which of the following statements are true.

- (a)  $A \perp B$
- (b)  $A \perp B | C$
- (c)  $A \perp B | \{C, D\}$
- (d)  $B \not\perp F$
- (e)  $B \perp F | E$
- (f)  $B \perp F | \{D, E\}$
- (g)  $F \perp G$
- (h)  $F \perp G | E$
- (i)  $F \perp G | \{A, E\}$

**Exercise 2.4.** Draw the graphs  $(\mathcal{G}_{\text{An}(A \cup B \cup S)})^m$  with  $\mathcal{G}$  given by the DAG in Figure 2.11 on page 33 and  $A, B, S$  given in Exercise 2.3(a)–(i), and verify your answers in Exercise 2.3 using the directed global Markov criterion.

---

## Probabilities

As mentioned in Chapter 2, probabilistic networks have a qualitative aspect and a corresponding quantitative aspect, where the qualitative aspect is given by a graphical structure in the form of an acyclic, directed graph (DAG) that represents the (conditional) dependence and independence properties of a joint probability distribution defined over a set of variables that are indexed by the vertices of the DAG.

The fact that the structure of a probabilistic network can be characterized as a DAG derives from basic axioms of probability calculus leading to recursive factorization of a joint probability distribution into a product of lower-dimensional conditional probability distributions. First, any joint probability distribution can be decomposed (or factorized) into a product of conditional distributions of different dimensionality, where the dimensionality of the largest distribution is identical to the dimensionality of the joint distribution.<sup>1</sup> This gives rise to a densely connected DAG. Second, statements of local conditional independences manifest themselves as reductions of dimensionalities of some of the conditional probability distributions. Most often, these independence statements give rise to dramatic reductions of complexity of the DAG such that the resulting DAG appears to be quite sparse.

In fact, a joint probability distribution,  $P$ , can be decomposed recursively in this fashion if and only if there is a DAG that correctly represents the (conditional) dependence and independence properties of  $P$ . This means that a set of conditional probability distributions specified according to a DAG,  $\mathcal{G} = (V, E)$ , (i.e., a distribution  $P(A|pa(A))$  for each  $A \in V$ ) define a joint probability distribution.

Therefore, a probabilistic network model can be specified either through direct specification of a joint probability distribution, or through a DAG (typically) expressing cause-effect relations and a set of corresponding conditional

---

<sup>1</sup> The dimensionality of a function is defined as the number of variables over which the function is defined.

probability distributions. Obviously, a model is almost always specified in the latter fashion.

This chapter presents some basic axioms of probability calculus from which the famous Bayes' rule follows as well as the chain rule for decomposing a joint probability distribution into a product of conditional distributions. We shall also present the fundamental operations needed to perform inference in probabilistic networks.

## 3.1 Basics

This section defines some basic concepts and axioms of Bayesian probability theory. These include events, conditional probability, and three basic axioms.

### 3.1.1 Events

The language of probabilities consists of statements (propositions) about probabilities of events. The probability of an event  $\mathbf{a}$  is denoted  $P(\mathbf{a})$ . An *event* can be considered as an outcome of an experiment (e.g., a coin flip), a particular observation of a value of a variable (or set of variables), an assignment of a value to a variable (or set of variables), etc. As a probabilistic network define a probability distribution over a set of variables,  $V$ , in our context an event is a configuration,  $\mathbf{x} \in \text{dom}(X)$ , (i.e., a vector of values) of a subset of variables  $X \subseteq V$ .

*Example 3.1 (Burglary or Earthquake, page 25).* Assume we observe  $W = \text{yes}$  and  $R = \text{yes}$ . This evidence is given by the event  $\varepsilon = (W = \text{yes}, R = \text{yes})$ , and the probability,  $P(\varepsilon)$  denotes the probability of this particular piece of evidence, namely that both  $W = \text{yes}$  and  $R = \text{yes}$  are observed.

### 3.1.2 Conditional Probability

The basic concept in the Bayesian treatment of uncertainty is that of *conditional probability*: Given event  $\mathbf{b}$ , the conditional probability of event  $\mathbf{a}$  is  $x$ , written as

$$P(\mathbf{a}|\mathbf{b}) = x.$$

This means that if  $\mathbf{b}$  is true and everything else known is irrelevant for  $\mathbf{a}$ , then the probability of  $\mathbf{a}$  is  $x$ .

*Example 3.2 (Burglary or Earthquake, page 25).* Assume that the alarm sounds in eight of every ten cases when there is an earthquake but no burglary. This fact would then be expressed as the conditional probability  $P(A = \text{yes}|B = \text{no}, E = \text{yes}) = 0.8$ .

### 3.1.3 Axioms

The following three axioms provide the basis for Bayesian probability calculus.

**Axiom 3.1.** *For any event,  $\mathbf{a}$ ,  $0 \leq P(\mathbf{a}) \leq 1$ , with  $P(\mathbf{a}) = 1$  if and only if  $\mathbf{a}$  occurs with certainty.*

**Axiom 3.2.** *For any two mutually exclusive events  $\mathbf{a}$  and  $\mathbf{b}$  the probability that either  $\mathbf{a}$  or  $\mathbf{b}$  occur is*

$$P(\mathbf{a} \text{ or } \mathbf{b}) \equiv P(\mathbf{a} \vee \mathbf{b}) = P(\mathbf{a}) + P(\mathbf{b}).$$

*In general, if events  $\mathbf{a}_1, \dots, \mathbf{a}_n$  are pairwise incompatible, then*

$$P\left(\bigcup_i^n \mathbf{a}_i\right) = P(\mathbf{a}_1) + \dots + P(\mathbf{a}_n) = \sum_i^n P(\mathbf{a}_i).$$

**Axiom 3.3.** *For any two events  $\mathbf{a}$  and  $\mathbf{b}$  the probability that both  $\mathbf{a}$  and  $\mathbf{b}$  occur is*

$$P(\mathbf{a} \text{ and } \mathbf{b}) \equiv P(\mathbf{a}, \mathbf{b}) = P(\mathbf{b}|\mathbf{a})P(\mathbf{a}) = P(\mathbf{a}|\mathbf{b})P(\mathbf{b}).$$

$P(\mathbf{a}, \mathbf{b})$  is called the joint probability of the events  $\mathbf{a}$  and  $\mathbf{b}$ .

Axiom 3.1 simply says that a probability is a non-negative real number less than or equal to 1, and that it equals 1 if and only if the associated event has happened for sure.

Axiom 3.2 says that if two events cannot co-occur, then the probability that either one of them occurs equals the sum of the probabilities of their individual occurrences.

Axiom 3.3 is sometimes referred to as the *fundamental rule* of probability calculus. The axiom says that the probability of the co-occurrence of two events,  $\mathbf{a}$  and  $\mathbf{b}$  can be computed as the product of the probability of event  $\mathbf{a}$  ( $\mathbf{b}$ ) occurring conditional on the fact that event  $\mathbf{b}$  ( $\mathbf{a}$ ) has already occurred and the probability of event  $\mathbf{b}$  ( $\mathbf{a}$ ) occurring.

*Example 3.3.* Consider the events “The cast of the die gives a 1” and “The cast of the die gives a 6”. Obviously, these events are mutually exclusive, and the probability that one of them is true equals the sum of the probabilities that the first event is true and that the second event is true. Thus, intuitively, Axiom 3.2 makes sense.

Note that if a set of events,  $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$ , is an exhaustive set of outcomes of some experiment (e.g., cast of a die), then  $\sum_i P(\mathbf{a}_i) = 1$ .

*Example 3.4 (Balls in An Urn).* Assume we have an urn with 2 red, 3 green, and 5 blue balls. The probabilities of picking a red, a green, or a blue ball are

$$P(\text{red}) = \frac{2}{10} = 0.2, \quad P(\text{green}) = \frac{3}{10} = 0.3, \quad P(\text{blue}) = \frac{5}{10} = 0.5.$$

By Axiom 3.2 on the previous page we get the probability of picking either a green or a blue ball:

$$P(\text{green or blue}) = P(\text{green}) + P(\text{blue}) = 0.8.$$

Similarly, the probability of picking either a red, a green, or a blue is 1. Without replacement, the color of the second ball depends on the color of the first ball. If we first pick a red ball (and keep it), then the probabilities of picking a red, a green, or a blue ball as the next one are, respectively,

$$P(\text{2nd-is-red} | \text{1st-was-red}) = \frac{2-1}{10-1} = \frac{1}{9},$$

$$P(\text{2nd-is-green} | \text{1st-was-red}) = \frac{3}{10-1} = \frac{3}{9},$$

$$P(\text{2nd-is-blue} | \text{1st-was-red}) = \frac{5}{10-1} = \frac{5}{9}.$$

By Axiom 3.3 on the preceding page we get the probability that the 1st ball is red and the 2nd is red:

$$\begin{aligned} P(\text{1st-was-red, 2nd-is-red}) &= P(\text{2nd-is-red} | \text{1st-was-red})P(\text{1st-was-red}) \\ &= \frac{1}{9} \cdot \frac{1}{5} = \frac{1}{45} \end{aligned}$$

Similarly, the probabilities that the 1st ball is red and the 2nd is green/blue are

$$\begin{aligned} P(\text{1st-was-red, 2nd-is-green}) &= P(\text{2nd-is-green} | \text{1st-was-red})P(\text{1st-was-red}) \\ &= \frac{1}{3} \cdot \frac{1}{5} = \frac{1}{15}, \end{aligned}$$

$$\begin{aligned} P(\text{1st-was-red, 2nd-is-blue}) &= P(\text{2nd-is-blue} | \text{1st-was-red})P(\text{1st-was-red}) \\ &= \frac{5}{9} \cdot \frac{1}{5} = \frac{1}{9}, \end{aligned}$$

respectively.

### 3.2 Probability Distributions for Variables

Probabilistic networks are defined over a (finite) set of variables, each of which represents a finite set of exhaustive and mutually exclusive states (or events); see Section 2.2 on page 20. Thus, (conditional) probability distributions for variables (i.e., over exhaustive sets of mutually exclusive events) play a very central role in probabilistic networks.

If  $X$  is a (random) variable with domain  $\text{dom}(X) = (x_1, \dots, x_{||X||})$ , then  $P(X)$  denotes a probability distribution (i.e., a vector of probabilities summing to 1), where

$$P(X) = (P(X = x_1), \dots, P(X = x_{||X||})) .$$

If no confusion is possible, we shall often use  $P(x)$  as short for  $P(X = x)$ , etc.

If the probability distribution for a variable  $Y$  is given conditional on a variable (or set of variables)  $X$ , then we shall use the notation  $P(Y|X)$ . That is, for each possible value (state),  $x \in \text{dom}(X)$ , we have a probability distribution  $P(Y|X = x)$ ; again, if no confusion is possible, we shall often write  $P(Y|x)$ .

*Example 3.5 (Balls in An Urn, page 39).* Let  $X_1$  represent the following exhaustive set of mutually exclusive events:

$$\text{dom}(X_1) = \{ \text{“1st ball is red”}, \text{“1st ball is green”}, \text{“1st ball is blue”} \}.$$

If we define  $X_1$  to denote the random variable “The color of the 1st ball drawn from the urn”, then we may define  $\text{dom}(X_1) = \{\text{red, green, blue}\}$ . Similarly, if we define  $X_2$  to denote the random variable “The color of the 2nd ball drawn from the urn”, then  $\text{dom}(X_2) = \text{dom}(X_1)$ . From Example 3.4 on page 39 we get

$$P(X_1) = \left( \frac{2}{10}, \frac{3}{10}, \frac{5}{10} \right),$$

$$P(X_2|X_1 = \text{red}) = \left( \frac{1}{9}, \frac{3}{9}, \frac{5}{9} \right).$$

$P(X_2|X_1)$  can be described in terms of a table of three (conditional) distributions:

	$X_1 = \text{red}$	$X_1 = \text{green}$	$X_1 = \text{blue}$
$P(X_2 X_1) =$			
$X_2 = \text{red}$	$\frac{1}{9}$	$\frac{2}{9}$	$\frac{2}{9}$
$X_2 = \text{green}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{3}{9}$
$X_2 = \text{blue}$	$\frac{5}{9}$	$\frac{5}{9}$	$\frac{4}{9}$

Note that the probabilities in each column sum to 1.

### 3.2.1 Rule of Total Probability

Let  $P(X, Y)$  be a joint probability distribution for two variables  $X$  and  $Y$  with  $\text{dom}(X) = \{x_1, \dots, x_m\}$  and  $\text{dom}(Y) = \{y_1, \dots, y_n\}$ . Using the fact that  $\text{dom}(X)$  and  $\text{dom}(Y)$  are exhaustive sets of mutually exclusive states of  $X$  and  $Y$ , respectively, Axiom 3.2 on page 39 gives us the *rule of total probability*:

$$\forall i: P(x_i) = P(x_i, y_1) + \dots + P(x_i, y_n) = \sum_{j=1}^n P(x_i, y_j). \quad (3.1)$$

Using Equation 3.1, we can calculate  $P(X)$  from  $P(X, Y)$ :

$$P(X) = \left( \sum_{j=1}^n P(x_1, y_j), \dots, \sum_{j=1}^n P(x_m, y_j) \right).$$

In a more compact notation, we may write  $P(X)$  as

$$P(X) = \sum_{j=1}^n P(X, y_j),$$

or even shorter as

$$P(X) = \sum_Y P(X, Y), \quad (3.2)$$

denoting the fact that we sum over all indices of  $Y$ . We shall henceforth refer to the operation in Equation 3.2 as *marginalization* or *projection*.<sup>2</sup> Also, we sometimes refer to this operation as “marginalizing out  $Y$ ” of  $P(X, Y)$ .

*Example 3.6 (Balls in An Urn, page 39).* Using Axiom 3.3 on page 39 for each combination of states of  $X_1$  and  $X_2$  of Example 3.5 on the preceding page, we can compute

$$\begin{aligned} P(X_1 = \text{red}, X_2 = \text{red}) &= P(X_1 = \text{red})P(X_2 = \text{red} | X_1 = \text{red}) \\ &= \frac{2}{10} \cdot \frac{1}{9} \\ &= \frac{1}{45}, \end{aligned}$$

etc. That is, we get  $P(X_1, X_2)$  by combining  $P(X_1)$  and  $P(X_2 | X_1)$ :

		$X_1 = \text{red}$	$X_1 = \text{green}$	$X_1 = \text{blue}$
$P(X_1, X_2) =$	$X_2 = \text{red}$	$\frac{1}{45}$	$\frac{1}{15}$	$\frac{1}{9}$
	$X_2 = \text{green}$	$\frac{1}{15}$	$\frac{1}{15}$	$\frac{1}{6}$
	$X_2 = \text{blue}$	$\frac{1}{9}$	$\frac{1}{6}$	$\frac{2}{9}$

(Note that the numbers in the table sum to 1.) Now, through marginalization we get

$$\begin{aligned} P(X_2) &= P(X_1 = \text{red}, X_2) + P(X_1 = \text{green}, X_2) + P(X_1 = \text{blue}, X_2) \\ &= \begin{pmatrix} \frac{1}{45} \\ \frac{1}{15} \\ \frac{1}{9} \end{pmatrix} + \begin{pmatrix} \frac{1}{15} \\ \frac{1}{15} \\ \frac{1}{6} \end{pmatrix} + \begin{pmatrix} \frac{1}{9} \\ \frac{1}{6} \\ \frac{2}{9} \end{pmatrix} = \begin{pmatrix} \frac{5}{10} \\ \frac{3}{10} \\ \frac{1}{2} \end{pmatrix}. \end{aligned}$$

<sup>2</sup> See Section 3.3.3 on page 46 for more on marginalization.



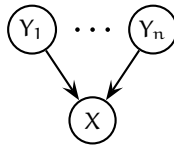
That is, the probabilities of getting a red, a green, and a blue ball in the second draw are, respectively, 0.2, 0.3, and 0.5, given that we know nothing about the color of the first ball. That is,  $P(X_2) = P(X_1) = (0.2, 0.3, 0.5)$ , whereas, for example,  $P(X_2|X_1 = \text{red}) = (0.1111, 0.3333, 0.5556)$ ; i.e., once the color of the first ball is known, our belief about the color of the second changes.

### 3.2.2 Graphical Representation

The conditional probability distributions of probabilistic networks are of the form

$$P(X|Y),$$

where  $X$  is a single variable and  $Y$  is a (possibly empty) set of variables.  $X$  and  $Y$  are sometimes called the *head* and the *tail*, respectively, of  $P(X|Y)$ . If  $Y = \emptyset$  (i.e., the empty set),  $P(X|Y)$  is often called a *marginal probability distribution* and is then written as  $P(X)$ . This relation between  $X$  and  $Y = \{Y_1, \dots, Y_n\}$  can be represented graphically as the DAG illustrated in Figure 3.1, where the child vertex is labelled “ $X$ ” and the parent vertices are labelled “ $Y_1$ ”, “ $Y_2$ ”, etc.



**Fig. 3.1.** Graphical representation of  $P(X|Y_1, \dots, Y_n)$ .

*Example 3.7 (Burglary or Earthquake, page 25).* Consider the variables  $B$  (Burglary),  $E$  (Earthquake), and  $A$  (Alarm), where  $B$  and  $E$  are possible causes of  $A$ . A natural way of specifying the probabilistic relations between these three variables, would be through a conditional probability distribution for  $A$  given  $B$  and  $E$ . Thus, for each combination of outcomes (states) of  $B$  and  $E$ , we need to specify a probability distribution over the states of  $A$ :

$P(A B, E) =$	$A$	$B = \text{no}$		$B = \text{yes}$	
		$E = \text{no}$	$E = \text{yes}$	$E = \text{no}$	$E = \text{yes}$
	no	0.99	0.1	0.1	0.01
	yes	0.01	0.9	0.9	0.99

This conditional probability table expresses the probability (whether obtained as an objective frequency or a subjective belief) of an alarm if either a burglary or an earthquake has taken place (but not both) to be 0.9, etc.

### 3.3 Probability Potentials

In working with probabilistic networks the notion of “potentials” often appears to be convenient. Formally, a *probability potential* is a non-negative function defined over the product space over the domains of a set of variables. We shall use Greek letters ( $\phi$ ,  $\psi$ , etc.) to denote potentials, and sometimes use subscripts to identify their domain (e.g.,  $\phi_X$  denotes a potential defined on  $\text{dom}(X)$ ) or to indicate that a potential  $\phi_X$  is a marginal potential of  $\phi$ .<sup>3</sup>

#### 3.3.1 Normalization

A (probability) potential,  $\phi_X$  defined on  $\text{dom}(X)$ , is turned into a probability distribution,  $P(X)$ , through the operation known as *normalization*. We shall use the notation  $\eta(\phi_X)$  to denote normalization of  $\phi_X$ , where  $\eta(\phi_X)$  is defined as

$$\eta(\phi_X) \triangleq \frac{\phi_X}{\sum_X \phi_X}. \quad (3.3)$$

Hence,  $P(X) = \eta(\phi_X)$ . The conditional probability distribution  $P(X|Y)$  can be obtained from the joint distribution  $P(X, Y)$  through *conditional normalization* with respect to  $X$ :

$$\eta_X(P(X, Y)) \triangleq \frac{P(X, Y)}{\sum_Y P(X, Y)} = P(Y|X).$$

In general,

$$\eta_{X'}(P(X)) \triangleq \frac{P(X)}{\sum_{X \setminus X'} P(X)} = P(X \setminus X' | X'), \quad (3.4)$$

where  $X'$  is a subset of the set of variables  $X$ . In particular,

$$\eta(P(X)) = \eta_\emptyset(P(X)) = P(X),$$

whenever  $P(X)$  is a probability distribution over  $X$ . This also holds true for conditional distributions:

$$\eta_Y(P(X|Y)) = P(X|Y),$$

since

$$\sum_X P(X|Y) = 1_Y, \quad (3.5)$$

where  $1_Y$  denotes a vector of 1s over  $\text{dom}(Y)$ . A uniform potential, e.g.  $1_Y$ , is called a *vacuous potential*. Intuitively, a vacuous potential can be thought of as a non-informative (or superfluous) potential.

We shall be using the notion of potentials extensively in Chapters 4 and 5, but for now we will just give a couple of simple examples illustrating the usefulness of this notion.

<sup>3</sup> Note that the two interpretations are consistent. See Section 3.3.3 on page 46 for details on marginalization.

*Example 3.8.* Let  $P(A, B) = P(A)P(B|A)$  be a factorization of the joint distribution for the Boolean variables  $A$  and  $B$ , and assume that  $P(A)$  and  $P(B|A)$  are given by the potentials  $\phi$  and  $\psi$ , respectively, where

$$\phi = (1, 2) \quad \text{and} \quad \psi = \begin{array}{c|cc} & B & \\ \hline & A = \text{false} & A = \text{true} \\ \hline \text{false} & 5 & 7 \\ \text{true} & 3 & 1 \end{array} .$$

Then

$$P(A) = \eta(\phi) = \left(\frac{1}{3}, \frac{2}{3}\right)$$

and

$$P(B|A) = \eta_A(\psi) = \begin{array}{c|cc} & B & \\ \hline & A = \text{false} & A = \text{true} \\ \hline \text{false} & \frac{5}{8} & \frac{7}{8} \\ \text{true} & \frac{3}{8} & \frac{1}{8} \end{array} .$$

Also,  $P(A, B) = \eta(\phi * \psi)$ .<sup>4</sup> Note, however, that for non-uniform normalization constants  $\sum_B \psi$  in  $\eta_A(\psi)$ , in general,  $P(A, B) \neq \eta(\phi * \psi)$ . In our case,  $\sum_B \psi = (8, 8)$ , and hence  $P(A, B) = \eta(\phi * \psi)$ .

### 3.3.2 Evidence Potentials

As indicated in Section 2.3 on page 23, evidence functions are actually potentials. To compute the joint posterior distribution resulting from incorporating a set of observations in the form of evidence functions, we simply extend the set of probability function constituents (possibly in the form of potentials) with corresponding evidence potentials, multiply, and normalize the product.

Before any evidence has been taken into account the probability distribution  $P(X')$  for a subset  $X' \subseteq X$  of variables is referred to as the *prior* probability distribution for  $X'$ . The conditional probability distribution  $P(X'|\varepsilon)$ , where  $\varepsilon$  denotes evidence, is referred to as the *posterior* probability distribution for  $X'$  given  $\varepsilon$ . Given an evidence potential  $\mathcal{E}_E$  on a subset  $E \subseteq X \setminus X'$  (expressing  $\varepsilon$ ), the posterior joint distribution is obtained as

$$P(X', \varepsilon) = \sum_{X \setminus X'} P(X) * \mathcal{E}_E,$$

and the posterior conditional distribution is achieved through normalization

$$P(X'|\varepsilon) = \eta(P(X', \varepsilon)).$$

We define  $P(X) * \mathcal{E}_E$  to have dimensionality  $|X \setminus E|$ . Thus, multiplication of  $P(X)$  with  $\mathcal{E}_E$  gives rise to a dimensionality decrease by  $|E|$ .

<sup>4</sup> See Section 3.3.3 for a definition of combination of potentials.

*Example 3.9 (Example 3.8 continued).* Assume that we observe  $B = \text{true}$ , represented by the evidence potential  $\mathcal{E}_B = (0, 1)$ . Then the posterior marginal distribution,  $P(A|\varepsilon)$ , is given by

$$P(A|\varepsilon) = \eta(\phi * \psi * \mathcal{E}_B) = \left(\frac{3}{5}, \frac{2}{5}\right),$$

where the two-dimensional potential  $\psi$  on  $A$  and  $B$  reduces to the one-dimensional potential  $(3, 1)$  on  $A$  when multiplied by the evidence potential  $\mathcal{E}_B$ .

### 3.3.3 Potential Calculus

To perform inference in probabilistic networks we only need a few simple operations, namely multiplication (combination), division, addition, and marginalization (projection). These are all defined very straightforwardly as follows.

Let  $\phi$  and  $\psi$  be potentials defined on  $\text{dom}(X)$  and  $\text{dom}(Y)$ , respectively, and let  $z \in \text{dom}(X \cup Y)$  be an arbitrary element (configuration).

We then define  $\phi * \psi$  as

$$(\phi * \psi)(z) \triangleq \phi(z_X)\psi(z_Y), \quad (3.6)$$

where  $z_X$  and  $z_Y$  are projections of  $z$  to  $\text{dom}(X)$  and  $\text{dom}(Y)$ , respectively.<sup>5</sup> Addition is defined analogously. We need to take special care to avoid division by zero, but otherwise division is defined in the obvious way:

$$(\phi/\psi)(z) \triangleq \begin{cases} 0 & \text{if } \phi(z_X) = 0 \\ \phi(z_X)/\psi(z_Y) & \text{if } \psi(z_Y) \neq 0 \\ \text{undefined} & \text{otherwise.} \end{cases} \quad (3.7)$$

As we shall see later, for all relevant operations involved in inference in probabilistic networks,  $\phi(z_X) = 0$  implies  $\psi(z_Y) = 0$  upon division of  $\phi$  by  $\psi$ , and thus, defining  $0/0 = 0$ , the division operator is always defined.

Let  $X' \subseteq X$  and let  $\phi$  be a potential defined on  $\text{dom}(X)$ . Then  $\phi_{X'} = \sum_{X \setminus X'} \phi$  denotes the marginalization (or projection) of  $\phi$  to  $\text{dom}(X')$  and is defined as

$$\phi_{X'}(x) \triangleq \sum_{z \in \text{dom}(X \setminus X')} \phi(z.x), \quad (3.8)$$

where  $z.x$  is the element in  $\text{dom}(X)$  for which  $(z.x)_{X \setminus X'} = z$  and  $(z.x)_{X'} = x$ .

*Example 3.10.* Let  $X = \{A, B\}$  and  $Y = \{B, C, D\}$ , where  $A, B, C, D$  are all binary variables with  $\text{dom}(A) = \{a_1, a_2\}$ , etc. Let  $\phi_X$  and  $\phi_Y$  be potentials defined over  $\text{dom}(X)$  and  $\text{dom}(Y)$ , respectively, where

<sup>5</sup> As defined in Section 2.2 on page 20.

$$\phi_X = \begin{array}{c|cc} & a_1 & a_2 \\ \hline b_1 & 0.1 & 0.9 \\ b_2 & 0.4 & 0.6 \end{array} \quad \text{and} \quad \phi_Y = \begin{array}{c|cc} & c_1 & c_2 \\ \hline d_1 & 0.11 & 0.14 \\ d_2 & 0.06 & 0.09 \end{array}.$$

From Equation 3.6 we get  $\psi = \phi_X * \phi_Y$  to be

$$\psi = \begin{array}{c|cccc} & & c_1 & & c_2 \\ \hline & d_1 & d_2 & d_1 & d_2 \\ \hline b_1 & (0.011, 0.099) & (0.014, 0.126) & (0.006, 0.054) & (0.009, 0.081) \\ b_2 & (0.092, 0.138) & (0.028, 0.042) & (0.072, 0.108) & (0.048, 0.072) \end{array},$$

where  $(\phi_X * \phi_Y)(a_1, b_1, c_1, d_1) = \phi_X(a_1, b_1)\phi_Y(b_1, c_1, d_1) = 0.1 \cdot 0.11 = 0.011$ ,  $(\phi_X * \phi_Y)(a_2, b_1, c_1, d_1) = \phi_X(a_2, b_1)\phi_Y(b_1, c_1, d_1) = 0.9 \cdot 0.11 = 0.099$ , etc.

Now, if  $Z = \{A, D\}$ , then from Equation 3.8 we get the marginal of  $\psi$  with respect to  $Z$  to be

$$\begin{aligned} \psi_Z &= \begin{array}{c|cc} & d_1 & d_2 \\ \hline a_1 & 0.011 + 0.092 + 0.006 + 0.072 & 0.014 + 0.028 + 0.009 + 0.048 \\ a_2 & 0.099 + 0.138 + 0.054 + 0.108 & 0.126 + 0.042 + 0.081 + 0.072 \end{array} \\ &= \begin{array}{c|cc} & d_1 & d_2 \\ \hline a_1 & 0.181 & 0.099 \\ a_2 & 0.399 & 0.321 \end{array}, \end{aligned}$$

where, for example,  $\psi_Z(a_1, d_1) = \psi((b_1, c_1).(a_1, d_1)) + \psi((b_2, c_1).(a_1, d_1)) + \psi((b_1, c_2).(a_1, d_1)) + \psi((b_2, c_2).(a_1, d_1)) = 0.011 + 0.092 + 0.006 + 0.072 = 0.181$ . Note that  $\psi$  (and hence also  $\psi_Z$ ) is a probability distribution (i.e.,  $\sum_x \psi(x) = 1$ ), since  $\phi_X$  is a conditional probability distribution for  $A$  given  $B$  and  $\phi_Y$  is a joint probability distribution for  $\{B, C, D\}$ .

### Distributive Law

Let  $\phi$  and  $\psi$  be potentials defined on  $\text{dom}(X) = \{x_1, \dots, x_m\}$  and  $\text{dom}(Y) = \{y_1, \dots, y_n\}$ , where  $X \cap Y = \emptyset$ . Using the distributive law, we then get

$$\begin{aligned}
\sum_{X \setminus X'} \sum_{Y \setminus Y'} (\phi * \psi) &= \sum_{x \in \text{dom}(X \setminus X')} \sum_{y \in \text{dom}(Y \setminus Y')} \phi(x) \psi(y) \\
&= \phi(x_1) \psi(y_1) + \cdots + \phi(x_1) \psi(y_n) + \cdots + \\
&\quad \phi(x_m) \psi(y_1) + \cdots + \phi(x_m) \psi(y_n) \\
&= \phi(x_1) [\psi(y_1) + \cdots + \psi(y_n)] + \cdots + \\
&\quad \phi(x_m) [\psi(y_1) + \cdots + \psi(y_n)] \\
&= \sum_{x \in \text{dom}(X \setminus X')} \phi(x) \sum_{y \in \text{dom}(Y \setminus Y')} \psi(y) \\
&= \sum_{X \setminus X'} \phi \sum_{Y \setminus Y'} \psi, \tag{3.9}
\end{aligned}$$

where  $X' \subseteq X$ ,  $Y' \subseteq Y$ , and  $\sum_X \phi \sum_Y \psi$  is short for  $\sum_X (\phi * (\sum_Y \psi))$ . Thus, if we wish to compute the marginal distribution  $(\phi * \psi)_{X' \cup Y'}$  and  $X \cap Y = \emptyset$ , then using the distributive law may help significantly in terms of reducing the computational complexity.

*Example 3.11.* Let  $\phi$ ,  $\psi$ , and  $\xi$  be potentials defined on  $\text{dom}(A, B, C)$ ,  $\text{dom}(B, D)$ , and  $\text{dom}(C, D, E)$ , respectively, and let  $\xi_E$  be an evidence potential defined on  $\text{dom}(E)$ , where the variables  $A, \dots, E$  are all binary. Assume that we wish to compute  $P(A|\varepsilon)$ , where  $\varepsilon$  denotes the evidence provided through  $\xi_E$ . A brute-force approach would be simply to combine all potentials, marginalize out variables  $B, \dots, E$ , and normalize:

$$P(A|\varepsilon) = \eta \left( \sum_B \sum_C \sum_D \sum_E (\phi * \psi * \xi * \xi_E) \right).$$

Combining potentials  $\xi$  and  $\xi_E$  requires 8 multiplications. Next, combining  $\psi$  and  $\xi * \xi_E$  requires 16 multiplications, and, finally, combining  $\phi$  and  $\psi * \xi * \xi_E$  requires 32 multiplications. Marginalizing out  $E$ ,  $D$ ,  $C$ , and  $B$ , respectively, require 16, 8, 4, and 2 additions.

Alternatively, we could take advantage of the distributive law to compute the same thing:

$$P(A|\varepsilon) = \eta \left( \sum_B \sum_C \phi \sum_D \psi \sum_E (\xi * \xi_E) \right).$$

First, combining  $\xi$  and  $\xi_E$  requires 8 multiplications. Then, marginalizing out  $E$  requires 4 additions. Multiplying the resulting potential by  $\psi$  requires 8 multiplications, and marginalizing out  $D$  requires 4 additions. Next, multiplying the resulting potential by  $\phi$  requires 8 multiplications, and finally, marginalizing out  $C$  and  $B$  requires 4 and 2 additions, respectively.

Summing up the number of arithmetic operations used in the two computations we find that the brute-force approach takes 56 multiplications and 30 additions, whereas the one exploiting the distributive law takes only 24

multiplications and 14 additions, less than half of what the brute-force approach requires. (On top of these numbers we should also count the number of operations needed to normalize the final marginal, but that is the same in both cases.)

Note that the ordering (B, C, D, E) is just one out of  $4! = 24$  different sequences in which we might marginalize out these four variables, and to each ordering is associated a certain number of arithmetic operations required to compute  $P(A|\varepsilon)$ .

The single most important key to efficient inference in probabilistic networks is the ability to take advantage of the distributive law (i.e., to find optimal (or near optimal) sequences in which the variables are marginalized out). We shall return to this issue in Chapter 5.

### 3.3.4 Barren Variables

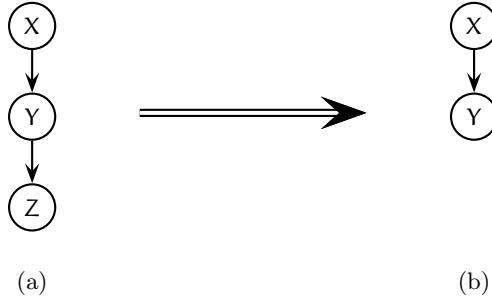
Variables of a probabilistic network that have no descendants and are never observed are called *barren variables*, as they provide no information relevant for the inference process. In fact, they provide “information” in the form of vacuous potentials (cf. Equation 3.5 on page 44), and may hence be removed from the network.

*Example 3.12.* Consider a model  $P(X, Y, Z) = P(X)P(Y|X)P(Z|Y)$  over the variables  $X$ ,  $Y$ , and  $Z$ . Following the discussion in Section 3.2.2 on page 43, this model can be represented graphically as indicated in Figure 3.2(a). Let  $\varepsilon_Y$  and  $\varepsilon_Z$  be evidence potentials for  $Y$  and  $Z$ , respectively, but where  $\varepsilon_Z$  is always vacuous. Then the posterior probability distribution for  $X$  can be calculated as

$$\begin{aligned} P(X|\varepsilon) &= \eta \left( \sum_Y P(Y|X) * \varepsilon_Y \sum_Z P(Z|Y) * \varepsilon_Z \right) \\ &= \eta \left( \sum_Y P(Y|X) * \varepsilon_Y \sum_Z P(Z|Y) \right) \\ &= \eta \left( \sum_Y P(Y|X) * \varepsilon_Y * 1_Y \right) \\ &= \eta \left( \sum_Y P(Y|X) * \varepsilon_Y \right), \end{aligned}$$

where  $\sum_Z P(Z|Y) = 1_Y$  follows from Equation 3.5 on page 44 and  $\varepsilon$  denotes the evidence. This means that the term  $P(Z|Y)$  can be neglected in the inference process, and the model can be simplified to the one shown in Figure 3.2(b), as variable  $Z$  is barren.

We shall return to the issue of barren variables in more detail in Section 5.1.1 on page 108.



**Fig. 3.2.** (a) Model for  $P(X, Y, Z)$ . (b) Equivalent model when  $Z$  is barren.

### 3.4 Fundamental Rule and Bayes' Rule

Generalizing Axiom 3.3 on page 39 to arbitrary (random) variables  $X$  and  $Y$  we get the *fundamental rule* of probability calculus:

$$P(X, Y) = P(X|Y)P(Y) = P(Y|X)P(X). \quad (3.10)$$

*Bayes' rule* follows immediately from Equation 3.10:

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}. \quad (3.11)$$

Using Axiom 3.3 on page 39 and the rule of total probability, Equation 3.11 can be rewritten as

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X|Y=y_1)P(Y=y_1) + \cdots + P(X|Y=y_n)P(Y=y_{||Y||})}.$$

That is, the denominator in Equation 3.11 can be derived from the numerator in Equation 3.11. Since, furthermore, the denominator is obviously the same for all states of  $Y$ , we often write Bayes' rule as

$$P(Y|X) \propto P(X|Y)P(Y), \quad (3.12)$$

read as “ $P(Y|X)$  is proportional to  $P(X|Y)P(Y)$ ”. Note that the proportionality factor  $P(X)^{-1}$  is in fact a vector of proportionality constants, one for each state of  $X$ , determined in a normalization operation.

Division by zero in Equation 3.11 is not a problem if we define  $0/0 = 0$ , since for

$$P(x_i) = \sum_j P(x_i|y_j)P(y_j)$$

to be zero at least one of  $P(x_i|y_j)$  and  $P(y_j)$  must be zero for each  $j$ , and if this is the case then both the numerator term,  $P(x_i|y_j)P(y_j)$ , and the denominator term,  $P(x_i)$ , of Equation 3.11 will be zero.



*Example 3.13 (Burglary or Earthquake, page 25).* Given  $P(E) = (0.01, 0.99)$ ,  $P(B) = (0.1, 0.9)$ , and the conditional probability table (CPT) for  $P(A|B, E)$  from Example 3.7 on page 43, we can use Bayes' rule to compute  $P(B|A)$ , the conditional probability distribution for burglary (B) given alarm (A):

$$P(B|A) \propto \sum_E P(A|B, E)P(B)P(E) = P(A, B).$$

First, we compute the joint distribution for A, B, and E:

$$\begin{aligned} P(A, B, E) &= P(A|B, E)P(B)P(E) \\ &= \begin{array}{c|cc|cc} & \text{B = no} & & \text{B = yes} & \\ & \text{E = no} & \text{E = yes} & \text{E = no} & \text{E = yes} \\ \hline \text{A} & & & & \\ \hline \text{no} & 0.88209 & 0.0009 & 0.0099 & 0.00001 \\ \text{yes} & 0.00891 & 0.0081 & 0.0891 & 0.00099 \end{array} \end{aligned}$$

Next, we marginalize out E of  $P(A, B, E)$  to obtain

$$P(A, B) = \sum_E P(A, B, E) = \begin{array}{c|cc} \text{A} & \text{B = no} & \text{B = yes} \\ \hline \text{no} & 0.88299 & 0.00991 \\ \text{yes} & 0.00991 & 0.09009 \end{array}.$$

Finally, we normalize  $P(A, B)$  with respect to A, and get

$$P(B|A) = \eta_A(P(A, B)) = \begin{array}{c|cc} \text{B} & \text{A = no} & \text{A = yes} \\ \hline \text{no} & 0.9889 & 0.1588 \\ \text{yes} & 0.0111 & 0.8412 \end{array}.$$

### 3.4.1 Interpretation of Bayes' Rule

Since Bayes' rule is so central to inference in Bayesian probability calculus, let us dwell a little on how Bayes' rule can be used and understood. Assume that we have two (possibly, sets of) variables X and Y, a model  $P(X, Y)$  given in the factorized form  $P(X|Y)P(Y)$ , and that we observe  $X = x$ . We would then typically want to compute  $P(Y|x)$ .

The prior distribution,  $P(Y)$ , expresses our initial belief about Y, and the posterior distribution,  $P(Y|x)$ , expresses our revised belief about Y in light of the observation  $X = x$ . Bayes' rule tells us how to obtain the posterior distribution by multiplying the prior  $P(Y)$  by the ratio  $P(x|Y)/P(x)$ , known as the *normalized likelihood* of Y given x. Again, since  $P(x)$  is a constant for each  $y \in \text{dom}(Y)$ , we get

$$P(Y|x) \propto P(Y)P(x|Y).$$

The quantity  $P(x|Y) \triangleq L(Y|x)$  is called the *likelihood* of Y given x. Hence, we have

$$P(Y|x) \propto P(Y)L(Y|x). \quad (3.13)$$

In general,

$$\text{posterior} \propto \text{prior} \times \text{likelihood}.$$

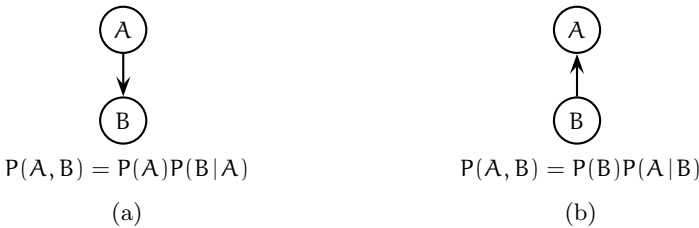
In a machine learning context, Bayes' rule plays an important role. For example, consider a prior distribution,  $P(M)$ , for a random variable  $M$ , expressing a set of possible models. For any value  $d$  of another variable  $D$ , expressing data, the quantity  $P(d|M)$  — considered as a function of  $M$  — is the likelihood function for  $M$  given data  $d$ . The posterior distribution for  $M$  given the data is then

$$P(M|d) \propto P(M)P(d|M),$$

which provides a set of goodness-of-fit measures for models  $M$  (i.e., we obtain a conditional probability  $P(m|d)$  for each  $m \in \text{dom}(M)$ ).

### Arc Reversal

Application of Bayes' rule can also be given a graphical interpretation. Consider, for example, two variables  $A$  and  $B$  and a model  $P(A, B) = P(A)P(B|A)$ . Again, following the discussion in Section 3.2.2 on page 43, this model can be represented graphically as indicated in Figure 3.3(a). Applying Bayes' rule on



**Fig. 3.3.** Two equivalent models that can be obtained from each other through arc reversal.

this model:

$$P(A|B) = \frac{P(A)P(B|A)}{\sum_A P(A)P(B|A)} = \frac{P(A, B)}{P(B)},$$

we obtain an equivalent model shown in Figure 3.3(b). Thus, one way of interpreting the application of Bayes' rule is through so-called *arc reversal*. As the typical inference task in probabilistic networks can be described as computing  $P(X|\varepsilon)$ , inference in probabilistic networks can be thought of as (repetitive) application of Bayes' rule or, in other words, as a sequence of arc reversals. Olmsted (1983) and Shachter (1990) have exploited this view of inference in his arc reversal algorithm for inference in probabilistic networks.

*Example 3.14 (Arc Reversal).* Consider the model in Figure 3.4(a), and assume that we wish to calculate the posterior marginal distribution for  $X$  given evidence,  $\mathcal{E}_Z$ , on  $Z$ . Using Shachter's arc reversal procedure we may proceed as follows:

$$\begin{aligned} P(X|\varepsilon) &= \eta \left( \sum_Y \sum_Z P(X)P(Y|X)P(Z|Y)\mathcal{E}_Z \right) \\ &= \eta \left( \sum_Y \sum_Z P(X)P(Y, Z|X)\mathcal{E}_Z \right) \end{aligned} \quad (3.14)$$

$$= \eta \left( \sum_Y \sum_Z P(X) \frac{P(Y, Z|X)}{\sum_Y P(Y, Z|X)} \sum_Y P(Y, Z|X)\mathcal{E}_Z \right) \quad (3.15)$$

$$= \eta \left( \sum_Y \sum_Z P(X)P(Y|X, Z)P(Z|X)\mathcal{E}_Z \right) \quad (3.16)$$

$$= \eta \left( \sum_Z P(X)P(Z|X)\mathcal{E}_Z \sum_Y P(Y|X, Z) \right) \quad (3.17)$$

$$= \eta \left( \sum_Z P(X)P(Z|X)\mathcal{E}_Z \right) \quad (3.18)$$

$$= \eta \left( \sum_Z \frac{P(X)P(Z|X)}{\sum_X P(X)P(Z|X)} \sum_X P(X)P(Z|X)\mathcal{E}_Z \right) \quad (3.19)$$

$$= \eta \left( \sum_Z P(X|Z)P(Z)\mathcal{E}_Z \right), \quad (3.20)$$

where we combine  $P(Y|X)$  and  $P(Z|Y)$  into  $P(Y, Z|X)$  (3.14), use Bayes' rule to reverse  $Y \rightarrow Z$  (3.15), which induces a new edge  $X \rightarrow Z$  (3.16), use the distributive law (3.17), eliminate barren variable  $Y$  (3.18), and finally use Bayes' rule to reverse  $X \rightarrow Z$  (3.19). Now, if  $\mathcal{E}_Z$  represent hard evidence (i.e.,  $Z = z$ ), (3.20) reduces to

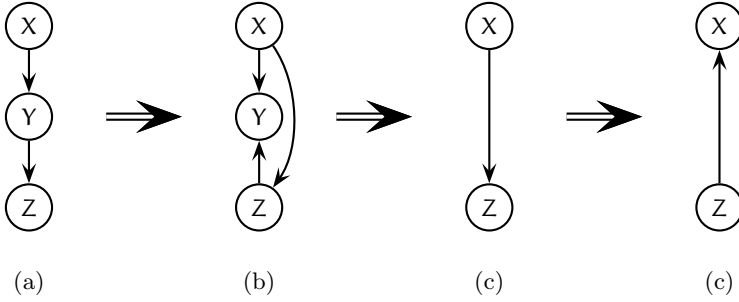
$$P(X|\varepsilon) = P(X|Z = z),$$

i.e., a simple look-up.

We shall return to the arc reversal approach in more detail in Section 5.1.1 on page 111.

### 3.5 Bayes' Factor

To calculate the relative support provided by an observation,  $Y = y$ , for two competing hypotheses,  $H_0 : X = x_0$  and  $H_1 : X = x_1$ , the notion of *Bayes' factor* is useful:



**Fig. 3.4.** (a) Model for  $P(X, Y, Z)$ . (b) Equivalent model obtained by reversing  $Y \rightarrow Z$ . (c) Equivalent model provided  $Y$  is barren. (d) Equivalent model obtained by reversing  $X \rightarrow Z$ .

$$B = \frac{\text{posterior odds}}{\text{prior odds}} = \frac{P(x_0 | y)/P(x_1 | y)}{P(x_0)/P(x_1)} = \frac{P(y | x_0)}{P(y | x_1)} = \frac{L(x_0 | y)}{L(x_1 | y)}; \quad (3.21)$$

that is, the ratio of the likelihoods of the two hypotheses given the observation. Bayes' factor is also known as the *Bayesian likelihood ratio*.

From Equation 3.21 we see that

- $B > 1$  if the observation provides more support for  $H_0$  than for  $H_1$ ,
- $B < 1$  if the observation provides less support for  $H_0$  than for  $H_1$ , and
- $B = 1$  if the observation does not provide useful information for differentiating between  $H_0$  and  $H_1$ .

*Example 3.15 (Balls in An Urn, page 39).* Let hypotheses  $H_0$  and  $H_1$  be given as

- $H_0$  : The second ball drawn will be green:  $X_2 = \text{green}$
- $H_1$  : The second ball drawn will be blue:  $X_2 = \text{blue}$ ,

and assume we observe that the first ball drawn is blue (i.e.,  $X_1 = \text{blue}$ ). Now, using the numbers calculated in Example 3.5 on page 41, we get the Bayes' factor

$$B = \frac{P(X_2 = \text{green} | X_1 = \text{blue})/P(X_2 = \text{blue} | X_1 = \text{blue})}{P(X_2 = \text{green})/P(X_2 = \text{blue})} = \frac{\frac{3}{9}/\frac{4}{9}}{\frac{3}{10}/\frac{5}{10}} = \frac{5}{4}.$$

That is, since the posterior odds (3/4) is greater than the prior odds (3/5), the observation provides more support for  $H_0$  than for  $H_1$ . Still, however, the probability that  $H_1$  is going to be true is greater than the probability that  $H_0$  is going to be true, as  $P(H_0 | X_1 = \text{blue}) = 3/9$  and  $P(H_1 | X_1 = \text{blue}) = 4/9$ .

### 3.6 Independence

A variable  $X$  is *independent* of another variable  $Y$  with respect to a probability distribution  $P$  if

$$P(x|y) = P(x), \forall x \in \text{dom}(X), \forall y \in \text{dom}(Y). \quad (3.22)$$

Using standard notation, we express this property symbolically as  $X \perp\!\!\!\perp_P Y$ , or simply as  $X \perp\!\!\!\perp Y$  when  $P$  is obvious from the context. Symmetry of independence (i.e.,  $X \perp\!\!\!\perp Y \equiv Y \perp\!\!\!\perp X$ ) can be verified from Bayes' rule:

$$P(x|y) = P(x) = \frac{P(y|x)P(x)}{P(y)} \Leftrightarrow P(y|x) = P(y).$$

The statement  $X \perp\!\!\!\perp Y$  is often referred to as *marginal independence* between  $X$  and  $Y$ .

A variable  $X$  is *conditionally independent* of  $Y$  given  $Z$  (with respect to a probability distribution  $P$ ) if

$$P(x|y, z) = P(x|z), \forall x \in \text{dom}(X), \forall y \in \text{dom}(Y), \forall z \in \text{dom}(Z). \quad (3.23)$$

The conditional independence statement expressed in Equation 3.23 is indicated as  $X \perp\!\!\!\perp Y|Z$  in the standard notation. With a slight misuse of notation, we shall also express this as  $P(X|Y, Z) = P(X|Z)$ .<sup>6</sup>

*Example 3.16 (Conditional Independence).* Consider the Burglary or Earthquake example from page 25. With  $P(R|E)$  given as

$R$	$E = \text{no}$	$E = \text{yes}$
no	0.999	0.01
yes	0.001	0.99

and  $P(A, E)$  given as in Example 3.13 on page 51 we get

$$\begin{aligned}
 P(A|E, R) &= \frac{P(A, E)P(R|E)}{\sum_A P(A, E)P(R|E)} \\
 &= \begin{array}{c|cc} & \text{R = no} & \text{R = yes} \\ \text{A} & \text{E = no} & \text{E = yes} & \text{E = no} & \text{E = yes} \\ \hline \text{no} & 0.901 & 0.091 & 0.901 & 0.091 \\ \text{yes} & 0.099 & 0.909 & 0.099 & 0.909 \end{array}
 \end{aligned}$$

and

$$P(A|E) = \frac{\sum_R P(A, E)P(R|E)}{\sum_{A, R} P(A, E)P(R|E)} = \begin{array}{c|cc} \text{A} & \text{E = no} & \text{E = yes} \\ \hline \text{no} & 0.901 & 0.091 \\ \text{yes} & 0.099 & 0.909 \end{array}.$$

Obviously,  $P(A|E, R) = P(A|E)$ . Thus, we conclude that  $A \perp\!\!\!\perp_P R|E$ .

<sup>6</sup> The misuse is concerned with differences in dimensionalities of  $P(X|Y, Z)$  and  $P(X|Z)$ .

### 3.6.1 Independence and DAGs

Let  $P$  be a probability distribution over a set of variables  $V$  and let  $\mathcal{G} = (V, E)$  be a DAG. Then  $\mathcal{G}$  is said to be a *correct* representation of the independence properties of  $P$  if  $X_A \perp\!\!\!\perp_P X_B | X_S$  whenever  $A \perp_{\mathcal{G}} B | S$  for subsets  $A, B, S$  of  $V$ . In other words, if for each pair of unconnected variables  $u, v \in V$  in  $\mathcal{G}$  (i.e.,  $u \not\sim_{\mathcal{G}} v$ ) it holds true that there is a set  $S \subseteq V$  such that  $X_u \perp\!\!\!\perp_P X_v | X_S$ , then  $\mathcal{G}$  is a correct representation of the independence properties of  $P$ . For brevity we shall then say that “ $\mathcal{G}$  is correct with respect to  $P$ ”.

Note that a DAG that is correct with respect to a distribution  $P$  does not necessarily represent all independence properties of  $P$ . In fact, the complete graph is correct with respect to any distribution.

**Definition 3.1 (Correctness and Completeness).** *Let  $P$  be a probability distribution over a set of variables  $X_V$ , where  $\mathcal{G} = (V, E)$  is a DAG over the vertices that indexes these variables. Correctness and completeness of  $\mathcal{G}$  with respect to  $P$  are then defined as follows:*

*Correctness of  $\mathcal{G}$  with respect to  $P$ :*  $A \perp_{\mathcal{G}} B | S \implies X_A \perp\!\!\!\perp_P X_B | X_S.$

*Completeness of  $\mathcal{G}$  with respect to  $P$ :*  $A \perp_{\mathcal{G}} B | S \iff X_A \perp\!\!\!\perp_P X_B | X_S.$

If  $\mathcal{G}$  is correct with respect to  $P$ , then  $\mathcal{G}$  is said to be an *I-map* of  $P$ . If  $\mathcal{G}$  is complete with respect to  $P$ , then  $\mathcal{G}$  is said to be a *D-map* of  $P$ . If  $\mathcal{G}$  is both correct and complete with respect to  $P$ , then  $\mathcal{G}$  is said to be a *perfect map* of  $P$ .<sup>7</sup>

*Example 3.17.* Let  $X, Y$ , and  $Z$  be three variables for which  $X \perp\!\!\!\perp_P Y | Z$ . Following the ordering  $(X, Y, Z)$  and using the fundamental rule (see Equation 3.10 on page 50) twice yields

$$P(X, Y, Z) = P(X|Y, Z)P(Y|Z)P(Z).$$

Since  $X \perp\!\!\!\perp_P Y | Z$ , this can be simplified to

$$P(X, Y, Z) = P(X|Z)P(Y|Z)P(Z). \quad (3.24)$$

Similarly, following the orderings  $(X, Z, Y)$  and  $(Y, Z, X)$  we get, respectively,

$$P(X, Y, Z) = P(X|Z)P(Z|Y)P(Y) \quad (3.25)$$

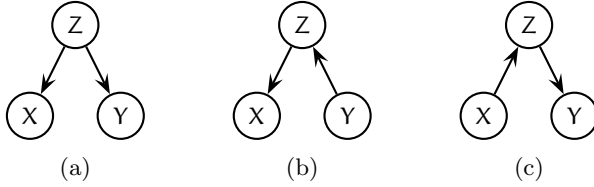
and

$$P(X, Y, Z) = P(Y|Z)P(Z|X)P(X). \quad (3.26)$$

Equations (3.24)–(3.26) have graphical representations as shown in Figures 3.5(a)–(c) (see Section 3.2.2 on page 43).

Only a subset of the independence properties that can exist in a probability distribution can be represented by a DAG. That is, the DAG language is not rich enough to simultaneously capture all sets of independence statements.

<sup>7</sup> “I” stands for “independence” and “D” stands for “dependence”.

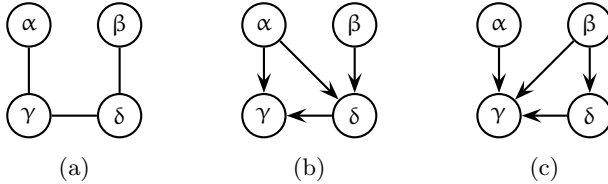


**Fig. 3.5.** Graphical representations of  $X \perp\!\!\!\perp_P Y | Z$ , representing, respectively, Equations (3.24)–(3.26).

*Example 3.18.* Consider the following set of independence statements for a probability distribution  $P$ :

$$\begin{aligned} \text{CID}_1 : \quad & X_\alpha \perp\!\!\!\perp_P X_\beta \\ \text{CID}_2 : \quad & X_\alpha \perp\!\!\!\perp_P X_\delta | \{X_\beta, X_\gamma\} \\ \text{CID}_3 : \quad & X_\beta \perp\!\!\!\perp_P X_\gamma | \{X_\alpha, X_\delta\}. \end{aligned}$$

From these statements we can conclude that a DAG,  $\mathcal{G}$ , over  $\{\alpha, \beta, \gamma, \delta\}$  must include edges between each pair of vertices except  $(\alpha, \beta)$ ,  $(\alpha, \delta)$ , and  $(\beta, \gamma)$ , as at least one independence statement has been specified for each of the variable pairs  $\{X_\alpha, X_\beta\}$ ,  $\{X_\alpha, X_\delta\}$ , and  $\{X_\beta, X_\gamma\}$ , respectively. A preliminary skeleton of the possible DAGs therefore appears as shown in Figure 3.6(a).



**Fig. 3.6.** (a) Preliminary skeleton for the independence statements of Example 3.18. (b) DAG representing  $\text{CID}_1$  and  $\text{CID}_3$ . (c) DAG representing  $\text{CID}_1$  and  $\text{CID}_2$ .

Recalling the d-separation criterion or the directed global Markov criterion (see Section 2.6 on page 31) we see that for  $\text{CID}_1$  to hold true there must be a converging connection at  $\gamma$  or  $\delta$ . However, a converging connection at e.g.  $\gamma$  implies  $\alpha \perp_\mathcal{G} \delta$ , violating correctness of  $\mathcal{G}$ . To remedy that, we will have to include an edge between  $\alpha$  and  $\delta$ . Now, to ensure  $\alpha \perp_\mathcal{G} \beta$ , the edges  $\alpha - \delta$  and  $\beta - \delta$  must meet head-to-head at  $\delta$  (i.e., must converge at  $\delta$ ). The resulting DAG in Figure 3.6(b) is correct with respect to  $P$  but not complete as  $\text{CID}_2$  is not represented. Similarly, the DAG in Figure 3.6(c) represents  $\text{CID}_1$  and  $\text{CID}_2$  but not  $\text{CID}_3$ .

The DAGs in Figures 3.6(b) and 3.6(c) correctly represent the independence statements of  $P$ ; neither of the DAGs, however, represents all three statements.

### 3.7 Chain Rule

For a probability distribution,  $P(X)$ , over a set of variables  $X = \{X_1, \dots, X_n\}$ , we can use the fundamental rule repetitively to decompose it into a product of conditional probability distributions:

$$\begin{aligned}
 P(X) &= P(X_1 | X_2, \dots, X_n) P(X_2, \dots, X_n) \\
 &= P(X_1 | X_2, \dots, X_n) P(X_2 | X_3, \dots, X_n) \cdots P(X_{n-1} | P_n) P(X_n) \\
 &= \prod_{i=1}^n P(X_i | X_{i+1}, \dots, X_n). \tag{3.27}
 \end{aligned}$$

Notice that the actual conditional distributions that comprise the factors of the decomposition are determined by the order in which we select the head variables of the conditional distributions. Thus, there are  $n$  factorial different factorizations of  $P(X)$ , and to each factorization corresponds a unique DAG, but all of these DAGs are equivalent in terms of dependence and independence properties, as they are all complete graphs, and hence represent no independence statements.

*Example 3.19 (Chain Decomposition and DAGs).* Let  $V = \{\alpha, \beta, \gamma, \delta\}$ . Then  $P(X_V)$  factorizes as

$$\begin{aligned}
 P(X_V) &= P(X_\alpha, X_\beta, X_\gamma, X_\delta) = P(X_\alpha | X_\beta, X_\gamma, X_\delta) P(X_\beta, X_\gamma, X_\delta) \\
 &= P(X_\alpha | X_\beta, X_\gamma, X_\delta) P(X_\beta | X_\gamma, X_\delta) P(X_\gamma, X_\delta) \\
 &= P(X_\alpha | X_\beta, X_\gamma, X_\delta) P(X_\beta | X_\gamma, X_\delta) P(X_\gamma | X_\delta) P(X_\delta) \tag{3.28}
 \end{aligned}$$

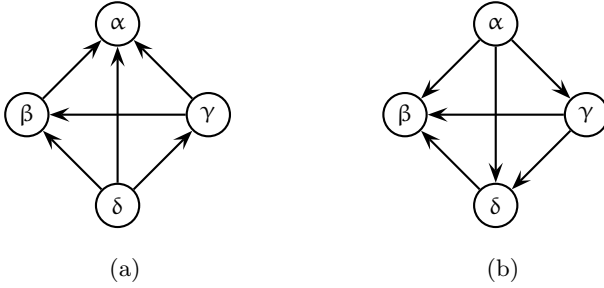
$$\begin{aligned}
 &= P(X_\beta | X_\alpha, X_\gamma, X_\delta) P(X_\delta | X_\alpha, X_\gamma) P(X_\gamma | X_\alpha) P(X_\alpha) \tag{3.29} \\
 &= \dots
 \end{aligned}$$

The DAGs corresponding to Equations (3.28) and (3.29) appear in Figures 3.7(a) and 3.7(b), respectively.

Assume that  $\mathcal{G}$  is a DAG that correctly represents the (conditional) dependence and independence properties of  $P$  (if any), and that the order in which we select the head variables of the conditional distributions respect a topological ordering  $(X_{v_1}, \dots, X_{v_n})$ <sup>8</sup> with respect to  $\mathcal{G}$ :  $\text{pa}(v_i) \subseteq \{v_1, \dots, v_{i-1}\}$  for all  $i = 1, \dots, n$  (i.e., the parents of each variable are selected before the variable itself). That is, the tail variables always include the parents.

<sup>8</sup> For notational convenience, we assume (without loss of generality) that  $v_1, \dots, v_n$  is a topological ordering.



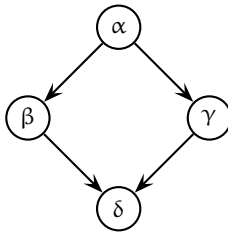


**Fig. 3.7.** (a) DAG corresponding to Equation (3.28). (b) DAG corresponding to Equation (3.29).

It follows easily from the d-separation criterion or the directed Markov criterion (Section 2.6 on page 31) that for any vertex  $v$  of a DAG,  $\mathcal{G}$ ,  $v \perp_{\mathcal{G}} \text{nd}(v) | \text{pa}(v)$ .<sup>9</sup> Since  $\mathcal{G}$  correctly represents the dependence and independence properties of  $P$ , it follows that  $X_v \perp_{\mathcal{P}} \text{nd}(X_v) | X_{\text{pa}(v)}$ . Therefore, each term  $P(X_{v_i} | X_{v_1}, \dots, X_{v_i})$  can be reduced to  $P(X_{v_i} | X_{\text{pa}(v_i)})$ . The product in Equation 3.27 then simplifies to the *chain rule*:

$$P(X_V) = \prod_{i=1}^n P(X_{v_i} | X_{\text{pa}(v_i)}). \quad (3.30)$$

*Example 3.20 (Example 3.19 continued).* Assume that the complete set of independence properties that  $P$  satisfies comprises  $\{X_\beta \perp_{\mathcal{P}} X_\gamma | X_\alpha, X_\alpha \perp_{\mathcal{P}} X_\delta | \{X_\beta, X_\gamma\}\}$ . Then the DAG in Figure 3.8 correctly (and completely) repre-



**Fig. 3.8.** DAG that correctly (and completely) represents the set of independence properties  $\{X_\beta \perp_{\mathcal{P}} X_\gamma | X_\alpha, X_\alpha \perp_{\mathcal{P}} X_\delta | \{X_\beta, X_\gamma\}\}$  of a distribution  $P$ ; see Example 3.20.

sents this set of independence properties. From the chain rule we can therefore write the joint distribution as

<sup>9</sup> This result is probably easiest to acknowledge from the directed Markov criterion: The graph  $(\mathcal{G}_{\text{An}(\{v\} \cup \text{nd}(v) \cup \text{pa}(v))})^m$  obviously excludes all descendants of  $v$  forcing all paths to  $v$  to go through  $\text{pa}(v)$ .

$$P(X_V) = P(X_\alpha)P(X_\beta|X_\alpha)P(X_\gamma|X_\alpha)P(X_\delta|X_\beta, X_\gamma),$$

where the tail variables are exactly the set of parents for each head variable.

### 3.8 Summary

Bayesian probability calculus is based on a few very simple and intuitive axioms that express ground statements of probability about the occurrence of a single event, the occurrence of mutually exclusive events, and the co-occurrence of events. Being defined, basically, as exhaustive lists of mutually exclusive events, (discrete) variables hence provide an excellent concept on which to base a calculus of distributions of probabilities. For example, we saw how the axiom on mutually exclusive events implies the rule of total probability, which is the basis for computing a (lower-dimensional) marginal probability distribution through projection from a (higher-dimensional) distribution. Together with the straightforward operations of multiplication (combination), division, and addition, the projection (or marginalization) operation provide a complete set of operations for probabilistic inference.

As a matter of convenience, the notion of probability potentials was introduced as a generalization of probability distributions in the sense that the elements of a probability potential do not necessarily sum to 1. Probability distributions are restored through the operation of normalization, where the normalization constant expresses the reciprocal value of the probability of the evidence.

The fundamental trick in making efficient probabilistic inference with a joint probability distribution over a (possibly large) collection of discrete random variables lies in the ability to exploit the (conditional) independence properties of the distribution. The extent to which these properties allow a factorization of the distribution into lower-dimensional distributions (i.e., distributions defined on subsets of the variables) determines how efficiently inference can be performed. Basically, this gain in efficiency is realized through the exploitation of the distributive law, which implies interleaving of the operations of combination and marginalization. Allowing a marginalization operation (dimensionality decrease) to be performed before a combination operation (dimensionality increase) reduces the total amount of arithmetic operations needed.

The ability to perform abductive reasoning in probabilistic inference (e.g., to compute  $P(X|Y = y)$  given  $P(Y|X)$  and  $P(X)$ ) follows from Bayes' rule, which in turn follows from the fundamental rule of probability calculus that is a generalization of the axiom on the co-occurrence of events. An often-used interpretation of Bayes' rule states that the posterior probability of an event given some observation, say  $P(X = x|Y = y)$  (i.e., our belief about the probability of the occurrence of the event  $X = x$  *after* the event  $Y = y$  has been observed), is proportional to the prior probability of the event,  $P(X = x)$  (i.e.,

our belief about the probability of the occurrence of the event  $X = x$  *before* observing  $Y = y$ ), times the likelihood of the event given the observation, defined as  $L(X = x|Y = y) = P(Y = y|X = x)$ .

We saw how to establish the important connection between the notion of d-separation (and the equivalent directed, global Markov property) defined on a DAG,  $\mathcal{G} = (V, E)$ , as discussed in Chapter 2, and the independence properties of a joint probability distribution,  $P$ , defined over variables represented by  $V$ , where the directed edges,  $E$ , lead from nodes representing tail variables to nodes representing head variables of conditional probability distributions constituting a factorization of  $P$ . In fact, with  $\mathcal{G}$  so defined, there is a one-to-one correspondence between the statements of d-separation in  $\mathcal{G}$  and the (conditional) independence statements of  $P$  (i.e.,  $\mathcal{G}$  is a correct and complete representation of the independence properties of  $P$ ). This correspondence between d-separation and (conditional) independence is expressed in the chain rule on page 59.<sup>10</sup>

On the basis of the fundamental concepts introduced in Chapters 2 and 3 we shall see in Chapters 4 and 5, respectively, how different kinds of probabilistic networks can be defined and how inference in these can be performed.

## Exercises

**Exercise 3.1.** Assume that a non-red ball is removed from the urn in Example 3.4 on page 39. What is then the probability of picking a blue ball from the urn?

**Exercise 3.2.** Assume that smoking ( $S = \text{true}$ ) causes lung cancer ( $L = \text{true}$ ) in one out every ten cases and that non-smokers ( $S = \text{false}$ ) get lung cancer in one out of 500 cases.

- (a) Specify the probability table for  $P(L|S)$ .
- (b) Assuming that smoking is the only cause of lung cancer, what is then the frequency of lung cancer in a population, where one third of the population are smokers?

**Exercise 3.3.** Suppose we have the simple model  $X \rightarrow Y$ , and are given  $P(X)$ ,  $P(Y|X)$ , and evidence  $Y = y$ .

- (a) Indicate a minimal-cost procedure for computing  $P(X|Y = y)$ .
- (b) Use the procedure to compute  $P(S|L = \text{true})$  in Exercise 3.2.

---

<sup>10</sup> Special cases in which variables are independent only for particular values of some other variable(s) might exist. Such *context-specific independence* properties obviously cannot be captured by a DAG. Thus, the one-to-one correspondence should be understood with respect to independence statements on the “level of variables”.

**Exercise 3.4.** Normally, John arrives on time at his office. If, however, the roads are icy, there is a chance that he will be late. Let  $I = \text{icy}$  denote the event that the roads are icy, and let  $L = \text{late}$  denote the event that John is late. Assume that our prior knowledge about road conditions (i.e., without knowing when John arrives) is given by  $P(I) = P(I = \text{icy}, I = \neg\text{icy}) = (0.01, 0.99)$ . Also, assume our experience tells us that  $P(L = \text{late} | \text{icy}) = 0.9$  and  $P(L = \text{late} | \neg\text{icy}) = 0.2$ .

- (a) What is the likelihood for icy roads given that John arrives late?
- (b) What is the probability of icy roads given that John arrives late?

**Exercise 3.5.** Assume that the complete list of conditional independence statements satisfied by a probability distribution  $P(A, B, C, D, E)$  is given by:

$$\begin{array}{lll}
 A \perp\!\!\!\perp D | \{B, C\} & B \perp\!\!\!\perp C | A & D \perp\!\!\!\perp E | C \\
 A \perp\!\!\!\perp D | \{B, C, E\} & B \perp\!\!\!\perp C | \{A, E\} & D \perp\!\!\!\perp E | \{B, C\} \\
 A \perp\!\!\!\perp E | C & B \perp\!\!\!\perp E | A & D \perp\!\!\!\perp E | \{A, C\} \\
 A \perp\!\!\!\perp E | \{B, C\} & B \perp\!\!\!\perp E | C & D \perp\!\!\!\perp E | \{A, B, C\} \\
 A \perp\!\!\!\perp E | \{C, D\} & B \perp\!\!\!\perp E | \{A, C\} & \\
 A \perp\!\!\!\perp E | \{B, C, D\} & B \perp\!\!\!\perp E | \{C, D\} & \\
 & B \perp\!\!\!\perp E | \{A, C, D\} & 
 \end{array}$$

- (a) Draw a DAG fulfilling the assumptions.
- (b) How many DAGs fulfill the assumptions?
- (c) Make factorizations of  $P$  corresponding to the DAGs.

**Exercise 3.6.** Let  $W \subseteq U$ , and let  $\phi \equiv \phi_U$  be a potential defined on  $\text{dom}(U)$ , where  $U = \{A, B, C, D\}$ ,  $W = \{A, C\}$ , and all four variables are binary, where  $\text{dom}(A) = \{a_1, a_2\}$ , etc. Let  $\phi_U$  be given by the following table:

		$c_1$ $d_1$	$c_1$ $d_2$	$c_2$ $d_1$	$c_2$ $d_2$
$a_1$	$b_1$	0.0957	0.0672	0.0341	0.0513
$a_1$	$b_2$	0.1021	0.0162	0.0634	0.1287
$a_2$	$b_1$	0.0174	0.1297	0.0040	0.1089
$a_2$	$b_2$	0.0624	0.0776	0.0307	0.0107

- (a) Compute  $\phi_W$ .
- (b) Indicate the table for the evidence function  $\mathcal{E}_D$  (defined on  $\text{dom}(D)$ ), representing the evidence “ $D$  is in state  $d_1$ ”.
- (c) Compute  $\phi_U * \mathcal{E}_D$ .
- (d) Compute the normalization constant,  $\mu$ , in  $P(U|e) = \mu * \phi_U * \mathcal{E}_D$ .

## Probabilistic Networks

In this chapter we introduce probabilistic networks for reasoning and decision making under uncertainty.

Many real-life situations can be modeled as a domain of entities represented as random variables in a probabilistic network. A probabilistic network is a clever graphical representation of dependence and independence relations between random variables. A domain of random variables can, for instance, form the basis of a decision support system to help decision makers identify the most beneficial decision in a given situation.

A probabilistic network represents and processes probabilistic knowledge. The representational components of a probabilistic network are a qualitative and a quantitative component. The qualitative component encodes a set of (conditional) dependence and independence statements among a set of random variables, informational precedence, and preference relations. The statements of (conditional) dependence and independence, information precedence, and preference relations are visually encoded using a graphical language. The quantitative component, on the other hand, specifies the strengths of dependence relations using probability theory and preference relations using utility theory.

The graphical representation of a probabilistic network describes knowledge of a problem domain in a precise manner. The graphical representation is intuitive and easy to comprehend, making it an ideal tool for communication of domain knowledge between experts, users, and systems. For these reasons, the formalism of probabilistic networks is becoming an increasingly popular knowledge representation for reasoning and decision making under uncertainty.

Since a probabilistic network consists of two components, it is customary to consider its construction as a two-phase process: The construction of the qualitative component and subsequently the construction of the quantitative component. The qualitative component defines the structure of the quantitative component. As the first step, the qualitative structure of the model is constructed using a graphical language. This step consists of identifying

variables and relations between variables. As the second step, the parameters of the quantitative part as defined by the qualitative part are assessed.

In this book, we consider the subclass of probabilistic networks known as Bayesian networks and influence diagrams. Bayesian networks and influence diagrams are ideal knowledge representations for use in many situations involving reasoning and decision making under uncertainty. These models are often characterized as normative expert systems as they provide model-based domain descriptions, where the model is reflecting properties of the problem domain (rather than the domain expert) and probability calculus is used as the calculus for uncertainty.

A Bayesian network model representation of a problem domain can be used as the basis for performing inference and analysis about the domain. Decision options and utilities associated with these options can be incorporated explicitly into the model, in which case the model becomes an influence diagram, capable of computing expected utilities of all decision options given the information known at the time of decision. Bayesian networks and influence diagrams are applicable for a large range of domain areas with inherent uncertainty.

Section 4.1 considers Bayesian networks as probabilistic models for reasoning under uncertainty. We consider Bayesian network models containing discrete variables only and models containing a mixture of continuous and discrete variables. Section 4.2 considers influence diagrams as probabilistic networks for decision making under uncertainty. The influence diagram is a Bayesian network augmented with decision variables, informational precedence relations, and preference relations. We consider influence diagram models containing discrete variables only and models containing a mixture of continuous and discrete variables. In Section 4.3 object-oriented probabilistic networks are considered. An object-oriented probabilistic network is a flexible framework for building hierarchical knowledge representations using the notions of classes and instances. In Section 4.4 dynamic probabilistic networks are considered. A dynamic probabilistic network is a method for representing dynamic systems that are changing over time.

## 4.1 Reasoning Under Uncertainty

A probabilistic interaction model between a set of random variables may be represented as a joint probability distribution. Considering the case where random variables are discrete, it is obvious that the size of the joint probability distribution will grow exponentially with the number of variables as the joint distribution must contain one probability for each configuration of the random variables. Therefore, we need a more compact representation for reasoning about the state of large and complex systems involving a large number of variables.

To facilitate an efficient representation of a large and complex domain with many random variables, the framework of Bayesian networks uses a graphical representation to encode dependence and independence relations among the random variables. The dependence and independence relations induce a compact representation of the joint probability distribution. By representing the dependence and independence relations of a domain explicitly in a graph, a compact representation of the dependence and independence relations is obtained.

#### 4.1.1 Discrete Bayesian Networks

A (discrete) Bayesian network,  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$ , over variables,  $\mathcal{X}$ , consists of an acyclic, directed graph  $\mathcal{G} = (V, E)$  and a set of conditional probability distributions  $\mathcal{P}$ . Each node  $v$  in  $\mathcal{G}$  corresponds one-to-one with a discrete random variable  $X_v \in \mathcal{X}$  with a finite set of mutually exclusive states. The directed links  $E \subseteq V \times V$  of  $\mathcal{G}$  specify assumptions of conditional dependence and independence between random variables according to the d-separation criterion (see Proposition 2.4 on page 32).

There is a conditional probability distribution,  $P(X_v | X_{\text{pa}(v)}) \in \mathcal{P}$ , for each variable  $X_v \in \mathcal{X}$ . The set of variables represented by the parents,  $\text{pa}(v)$ , of  $v \in V$  in  $\mathcal{G} = (V, E)$  are sometimes called the *conditioning variables* of  $X_v$  — the *conditioned* variable.

**Definition 4.1.** (*Jensen 2001*) A (discrete) Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  consists of

- a DAG  $\mathcal{G} = (V, E)$  with nodes  $V = \{v_1, \dots, v_n\}$  and directed links  $E$
- a set of discrete random variables,  $\mathcal{X}$ , represented by the nodes of  $\mathcal{G}$
- a set of conditional probability distributions,  $\mathcal{P}$ , containing one distribution,  $P(X_v | X_{\text{pa}(v)})$ , for each random variable  $X_v \in \mathcal{X}$ .

A Bayesian network encodes a joint probability distribution over a set of random variables,  $\mathcal{X}$ , of a problem domain. The set of conditional probability distributions,  $\mathcal{P}$ , specifies a multiplicative factorization of the joint probability distribution over  $\mathcal{X}$  as represented by the chain rule of Bayesian networks (see Section 3.7 on page 58):

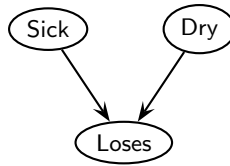
$$P(\mathcal{X}) = \prod_{v \in V} P(X_v | X_{\text{pa}(v)}). \quad (4.1)$$

Even though the joint probability distribution specified by a Bayesian network is defined in terms of conditional independence, a Bayesian network is most often constructed using the notion of cause–effect relations, see Section 2.4. In practice, cause–effect relations between entities of a problem domain can be represented in a Bayesian network using a graph of nodes representing random variables and links representing cause–effect relations between

the entities. Usually, the construction of a Bayesian network (or any probabilistic network for that matter) proceeds according to an iterative procedure where the set of nodes and their states, and the set of links are updated iteratively as the model becomes more and more refined. In Chapters 6 and 7, we consider in detail the art of building efficient probabilistic network representations of a problem domain.

To solve a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  is to compute all posterior marginals given a set of evidence  $\varepsilon$ , i.e.,  $P(X|\varepsilon)$  for all  $X \in \mathcal{X}$ . If the evidence set is empty, i.e.,  $\varepsilon = \emptyset$ , then the task is to compute all prior marginals, i.e.,  $P(X)$  for all  $X \in \mathcal{X}$ .

*Example 4.1 (Apple Jack (Madsen, Nielsen & Jensen 1998)).* Consider the small orchard belonging to Jack Fletcher (let us call him Apple Jack). One day Apple Jack discovers that his finest apple tree is *losing its leaves*. Apple Jack wants to know why this is happening. He knows that if the tree is *dry* (for instance, caused by a drought) there is no mystery as it is very common for trees to lose their leaves during a drought. On the other hand, the loss of leaves can be *an indication of a disease*.



**Fig. 4.1.** The Apple Jack network.

The qualitative knowledge about the cause-effect relations of this situation can be modeled by the DAG  $\mathcal{G}$  shown in Figure 4.1. The graph consists of three nodes: **Sick**, **Dry**, and **Loses** that represent variables of the same names. Each variable may be in one of two states: **no** and **yes**, i.e.,  $\text{dom}(\text{Dry}) = \text{dom}(\text{Loses}) = \text{dom}(\text{Sick}) = \{\text{no}, \text{yes}\}$ . The variable **Sick** tells us that the apple tree is sick by being in state **yes**. Otherwise, it will be in state **no**. The variables **Dry** and **Loses** tell us whether or not the tree is dry and whether or not the tree is losing its leaves, respectively.

The graph,  $\mathcal{G}$ , shown in Figure 4.1 models the cause-effect relations between variables **Sick** and **Loses** as well as between **Dry** and **Loses**. This is represented by the two (causal) links (**Sick**, **Loses**) and (**Dry**, **Loses**). In this way **Sick** and **Dry** are common causes of the effect **Loses**.

Let us return to the discussion of causality considered previously in Section 2.4. When there is a causal dependence relation going from a variable **A** to another variable **B**, we expect that when **A** is in a certain state this has an



impact on the state of B. One should be careful when modeling causal dependence relations in a Bayesian network. Sometimes it is not quite obvious in which direction a link should point. In the Apple Jack example, we say that there is a causal impact from Sick on Loses, because when a tree is sick this might cause the tree to lose its leaves. Why can we not say that when the tree loses its leaves it might be sick and turn the link in the other direction? The reason is that it is the sickness that causes the tree to lose its leaves and not the lost leaves that causes the sickness.

Figure 4.1 shows the graphical representation of the Bayesian network model. This is referred to as the qualitative representation. To have a complete Bayesian network, we need to specify the quantitative representation. Recall that each variable has two states, no and yes.

The quantitative representation of a Bayesian network is the set of conditional probability distributions,  $\mathcal{P}$ , defined by the structure of  $\mathcal{G}$ . Table 4.1 shows the conditional probability distribution of Loses given Sick and Dry, i.e.,  $P(\text{Loses}|\text{Dry}, \text{Sick})$ . For variables Sick and Dry we assume that  $P(S) = (0.9, 0.1)$  and  $P(D) = (0.9, 0.1)$  (we use D as short for Dry, S as short for Sick, and L as short for Loses).

D	S	L	
		no	yes
no	no	0.98	0.02
no	yes	0.1	0.9
yes	no	0.15	0.85
yes	yes	0.05	0.95

**Table 4.1.** The conditional probability distribution  $P(L|D, S)$ .

Note that all distributions specify the probability of a variable being in a specific state depending on the configuration of its parent variables, but since Sick and Dry do not have any parent variables, their distributions are marginal distributions.

The model may be used to compute all prior marginals and the posterior distribution of each non-evidence variable given evidence in the form of observations on a subset of the variables in the model. The priors for D and S equals the specified marginal distributions, i.e.,  $P(D) = P(S) = (0.9, 0.1)$ , while the prior distribution for L is computed through combination of the distributions specified for the three variables, followed by marginalization, where variables D and S are marginalized out. This yields  $P(L) = (0.82, 0.18)$  (see Example 3.10 on page 46 for details on combination and marginalization). Following a similar procedure, the posteriors of D and S given  $L = \text{yes}$  can be computed to be  $P(D|L = \text{yes}) = (0.53, 0.47)$  and  $P(S|L = \text{yes}) = (0.51, 0.49)$ .

Thus, according to the model the tree being sick is the most likely cause of the loss of leaves.

The specification of a conditional probability distribution  $P(X_v | X_{\text{pa}(v)})$  can be a labor-intensive knowledge acquisition task as the number of parameters grows exponentially with the size of  $\text{dom}(X_{\text{fa}(v)})$ , where  $\text{fa}(v) = \text{pa}(v) \cup \{v\}$ . Different techniques can be used to simplify the knowledge acquisition task, assumptions can be made, or the parameters can be estimated from data.

The complexity of a Bayesian network is defined in terms of the family  $\text{fa}(v)$  with the largest state space size  $\|X_{\text{fa}(v)}\| \triangleq |\text{dom}(X_{\text{fa}(v)})|$ . As the state space size of a family of variables grows exponentially with the size of the family, we seek to reduce the size of the parent sets to a minimum. Another useful measure of the complexity of a Bayesian network is the number of cycles and the length of cycles in its graph.

**Definition 4.2.** *A Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  is minimal if and only if, for every variable  $X_v \in \mathcal{X}$  and for every parent  $Y \in X_{\text{pa}(v)}$ ,  $X_v$  is not independent of  $Y$  given  $X_{\text{pa}(v)} \setminus \{Y\}$ .*

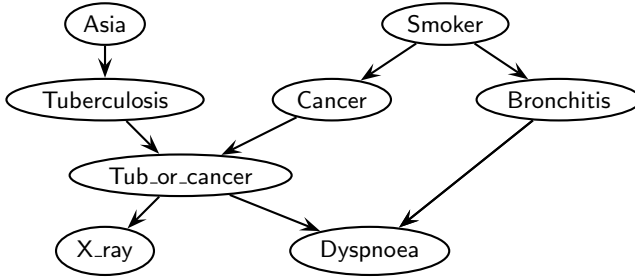
Definition 4.2 says that the parent set  $X_{\text{pa}(v)}$  of  $X_v$  should be limited to the set of variables with a direct impact on  $X_v$ .

*Example 4.2 (Chest Clinic (Lauritzen & Spiegelhalter 1988)).* A physician at a chest clinic wants to diagnose her patients with respect to three diseases based on observations of symptoms and possible causes of the diseases. The fictitious qualitative medical knowledge is the following.

The physician is trying to diagnose a patient who may be suffering from one or more of *tuberculosis*, *lung cancer*, or *bronchitis*. *Shortness-of-breath* (dyspnoea) may be due to tuberculosis, lung cancer, bronchitis, none of them, or more than one of them. *A recent visit to Asia* increases the chances of tuberculosis, while *smoking* is known to be a risk factor for both lung cancer and bronchitis. *The results of a single chest X-ray* do not discriminate between lung cancer and tuberculosis, as neither does the presence or absence of dyspnoea.

From the description of the situation it is clear that there are three possible diseases to consider (lung cancer, tuberculosis, and bronchitis). The three diseases produce three variables **Tuberculosis** (T), **Cancer** (L), and **Bronchitis** (B) with states **no** and **yes**. These variables are the targets of the reasoning and may, for this reason, be referred to as *hypothesis variables*. The diseases may be manifested in two symptoms (results of the X-ray and shortness-of-breath). The two symptoms produce two variables **X-ray** (X), and **Dyspnoea** (D) with states **no** and **yes**. In addition, there are two causes or risk factors (smoking and a visit to Asia) to consider. The two risk factors produce variables **Asia** (A) and **Smoker** (S) with states **no** and **yes**.

An acyclic, directed graph,  $\mathcal{G}$ , encoding the above medical qualitative knowledge is shown in Figure 4.2, where the variable **Tub\_or\_cancer** (E) is a



**Fig. 4.2.** A graph specifying the independence and dependence relations of the Asia example.

mediating variable (modeling trick, see Section 6.2.2 on page 150) specifying whether or not the patient has tuberculosis or lung cancer (or both).

Using the structure of  $\mathcal{G}$ , we may perform an analysis of dependence and independence properties between variables in order to ensure that the qualitative structure encodes the domain knowledge correctly. This analysis would be based on an application of the d-separation criterion.

Figure 4.2 only presents the qualitative structure  $\mathcal{G}$  (and the variables) of  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$ . In order to have a fully specified Bayesian network, it is necessary to specify the quantitative part,  $\mathcal{P}$ , too.

The quantitative domain knowledge is specified in the following set of (conditional) probability distributions  $P(A) = (0.99, 0.01)$ ,  $P(S) = (0.5, 0.5)$ , and the remaining conditional probability distributions, except  $P(E|L, T)$ , are shown in Tables 4.2 and 4.3.

$P(L S)$	$S = \text{no}$	$S = \text{yes}$	$P(B S)$	$S = \text{no}$	$S = \text{yes}$
$L = \text{no}$	0.99	0.9	$B = \text{no}$	0.7	0.4
$L = \text{yes}$	0.01	0.1	$B = \text{yes}$	0.3	0.6

$P(T A)$	$A = \text{no}$	$A = \text{yes}$	$P(X E)$	$E = \text{no}$	$E = \text{yes}$
$T = \text{no}$	0.99	0.95	$X = \text{no}$	0.95	0.02
$T = \text{yes}$	0.01	0.05	$X = \text{yes}$	0.05	0.98

**Table 4.2.** The conditional probability distributions  $P(L|S)$ ,  $P(B|S)$ ,  $P(T|A)$ , and  $P(X|E)$ .

The conditional probability table of the random variable  $E$  can be generated from a mathematical expression. From our domain knowledge of the diagnosis problem we know that  $E$  represents the disjunction of  $L$  and  $T$ . That is,  $E$  represents whether or not the patient has tuberculosis or lung cancer.

From this we can express  $E$  as  $E = T \vee L$ . This produces the conditional probability  $P(E = \text{yes} | L = l, T = t) = 1$  whenever  $l$  or  $t$  is **yes**.

	B = no		B = yes	
	E = no	E = yes	E = no	E = yes
D = no	0.9	0.3	0.2	0.1
D = yes	0.3	0.7	0.8	0.9

**Table 4.3.** The conditional probability distribution  $P(D | B, E)$ .

We will in a later section consider in more detail how to build mathematical expressions for the generation of conditional probability distributions (see Section 6.5.3 on page 166).

$\varepsilon$	$P(B = \text{yes}   \varepsilon)$	$P(L = \text{yes}   \varepsilon)$	$P(T = \text{yes}   \varepsilon)$
$\emptyset$	0.45	0.055	0.01
$\{S = \text{yes}\}$	0.6	0.1	0.01
$\{S = \text{yes}, D = \text{yes}\}$	0.88	0.15	0.015
$\{S = \text{yes}, D = \text{yes}, X = \text{yes}\}$	0.71	0.72	0.08

**Table 4.4.** Posterior distributions of the disease variables given various evidence scenarios.

Using the Bayesian network model just developed, we may compute the posterior probability of the three diseases given various subsets of evidence on the causes and symptoms as shown in Table 4.4.

### 4.1.2 Conditional Linear Gaussian Bayesian Networks

Up until now, we have considered Bayesian networks over discrete random variables only. However, there are many reasons for extending our considerations to include continuous variables. In this section we will consider Bayesian networks consisting of both continuous and discrete variables. For reasons to become clear later, we restrict our attention to the case of conditional linear Gaussian (also known as Normal) distributions and the case of conditional linear Gaussian Bayesian networks. We refer to a conditional linear Gaussian Bayesian network as a CLG Bayesian network.

A CLG Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{F})$  consists of an acyclic, directed graph  $\mathcal{G} = (V, E)$ , a set of conditional probability distributions  $\mathcal{P}$ , and a set of density functions  $\mathcal{F}$ . There will be one conditional probability distribution for each discrete random variable  $X$  of  $\mathcal{X}$  and one density function for each continuous random variable  $Y$  of  $\mathcal{X}$ .

A CLG Bayesian network specifies a distribution over a mixture of discrete and continuous variables (Lauritzen 1992b, Lauritzen & Jensen 2001). The variables,  $\mathcal{X}$ , are partitioned into the set of continuous variables,  $\mathcal{X}_\Gamma$ , and the set of discrete variables,  $\mathcal{X}_\Delta$ . Each node of  $\mathcal{G}$  represents either a discrete random variable with a finite set of mutually exclusive and exhaustive states or a continuous random variable with a conditional linear Gaussian distribution conditional on the configuration of its discrete parent variables. This implies an important constraint on the structure of  $\mathcal{G}$ , namely that a discrete random variable  $X_v$  may only have discrete parents, i.e.,  $X_{\text{pa}(v)} \subseteq \mathcal{X}_\Delta$  for any  $X_v \in \mathcal{X}_\Delta$ .

Any Gaussian distribution function can be specified by its mean and variance parameter. As mentioned above, we consider the case where a continuous random variable can have a single Gaussian distribution function for each configuration of its discrete parent variables. If a continuous variable has one or more continuous variables as parents, the mean may depend linearly on the state of the continuous parent variables. Continuous parent variables of discrete variables are disallowed.

A random variable,  $X$ , has a continuous distribution if there exists a non-negative function  $p$ , defined on the real line, such that for any interval  $J$ :

$$P(X \in J) = \int_J p(x) dx,$$

where the function  $p$  is the probability density function of  $X$  (DeGroot 1986). The probability density function of a *Gaussian* (or *Normal*) *distributed variable*,  $X$ , with a mean value,  $\mu$ , and a positive variance,  $\sigma^2$ , is (i.e.,  $X \sim \mathcal{N}(\mu, \sigma^2)$  or  $\mathcal{L}(X) = \mathcal{N}(\mu, \sigma^2)$ )

$$p(x; \mu, \sigma^2) = \mathcal{N}(x; \mu, \sigma^2) = \frac{1}{\sqrt{(2\pi\sigma^2)}} \exp \left[ -\frac{(x - \mu)^2}{2\sigma^2} \right],$$

where  $x \in \mathbb{R}$ .<sup>1</sup>

A continuous random variable,  $X$ , has a *conditional linear Gaussian distribution* (or CLG distribution), conditional on the configuration of the parent variables ( $Z \subseteq \mathcal{X}_\Gamma, I \subseteq \mathcal{X}_\Delta$ ) if

$$\mathcal{L}(X|Z = z, I = i) = \mathcal{N}(A(i) + B(i)^T z, C(i)), \quad (4.2)$$

where  $A$  is a table of mean values (one value for each configuration  $i$  of the discrete parent variables  $I$ ),  $B$  is a table of regression coefficient vectors (one vector for each configuration  $i$  of  $I$  with one regression coefficient for each continuous parent variable), and  $C$  is a table of variances (one for each configuration  $i$  of  $I$ ). Notice that the mean value  $A(i) + B(i)^T z$  of  $X$  depends linearly on the values of the continuous parent variables  $Z$ , while the variance is independent of  $Z$ . We allow for the situation where the variance is zero such that deterministic relations between continuous variables can be represented.

<sup>1</sup>  $\mathcal{L}(X)$  should be read as “the law of  $X$ ”.

The quantitative part of a CLG Bayesian network consists of a conditional probability distribution for each  $X \in \mathcal{X}_\Delta$  and a conditional Gaussian distribution for each  $X \in \mathcal{X}_\Gamma$ . For each  $X \in \mathcal{X}_\Gamma$  with discrete parents,  $I$ , and continuous parents,  $Z$ , we need to specify a one-dimensional Gaussian probability distribution for each configuration  $\mathbf{i}$  of  $I$  as shown in Equation 4.2.

**Definition 4.3.** A CLG Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{F})$  consists of

- a DAG  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with nodes  $\mathcal{V}$  and directed links  $\mathcal{E}$
- a set of random variables,  $\mathcal{X}$ , represented by the nodes of  $\mathcal{G}$
- a set of conditional probability distributions,  $\mathcal{P}$ , containing one distribution,  $P(X_v | X_{\text{pa}(v)})$ , for each discrete random variable  $X_v$
- a set of conditional-linear Gaussian probability density functions,  $\mathcal{F}$ , containing one density function,  $p(Y_v | X_{\text{pa}(v)})$ , for each continuous random variable  $Y_v$ .

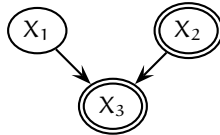
The joint distribution over all the variables in a CLG Bayesian network has the form  $P(\mathcal{X}_\Delta = \mathbf{i}) * \mathbb{N}_{|\mathcal{X}_\Gamma|}(\boldsymbol{\mu}(\mathbf{i}), \boldsymbol{\sigma}^2(\mathbf{i}))$ , where  $\mathbb{N}_k(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$  denotes a  $k$ -dimensional Gaussian distribution. The chain rule of CLG Bayesian networks is

$$P(\mathcal{X}_\Delta = \mathbf{i}) * \mathbb{N}_{|\mathcal{X}_\Gamma|}(\boldsymbol{\mu}(\mathbf{i}), \boldsymbol{\sigma}^2(\mathbf{i})) = \prod_{v \in \mathcal{V}_\Delta} P(\mathbf{i}_v | \mathbf{i}_{\text{pa}(v)}) * \prod_{w \in \mathcal{V}_\Gamma} p(\mathbf{y}_w | X_{\text{pa}(w)}),$$

for each configuration  $\mathbf{i}$  of  $\mathcal{X}_\Delta$ .

Recall that in the graphical representation of a CLG Bayesian network, continuous variables are represented by double ovals.

*Example 4.3.* Figure 4.3 shows an example of the qualitative specification of a CLG Bayesian network,  $\mathcal{N}$ , with three variables, i.e.,  $\mathcal{X} = \{X_1, X_2, X_3\}$ , where  $\mathcal{X}_\Delta = \{X_1\}$  and  $\mathcal{X}_\Gamma = \{X_2, X_3\}$ . Hence,  $\mathcal{N}$  consists of a continuous random variable  $X_3$  having one discrete random variable  $X_1$  (binary with states false and true) and one continuous random variable  $X_2$  as parents.



**Fig. 4.3.** CLG Bayesian network with  $X_1$  discrete, and  $X_2$  and  $X_3$  continuous.

To complete the model, we need to specify the relevant conditional probability distribution and density functions. The quantitative specification could, for instance, consist of the following conditional linear Gaussian distribution functions for  $X_3$

$$\begin{aligned}\mathcal{L}(X_3 | \text{false}, x_2) &= \mathcal{N}(-5 + (-2 * x_2), 1.1) \\ \mathcal{L}(X_3 | \text{true}, x_2) &= \mathcal{N}(5 + (2 * x_2), 1.2).\end{aligned}$$

The quantitative specification is completed by letting  $X_2$  have a standard Normal distribution (i.e.,  $X_2 \sim \mathcal{N}(0, 1)$ ) and  $P(X_1) = (0.75, 0.25)$ .

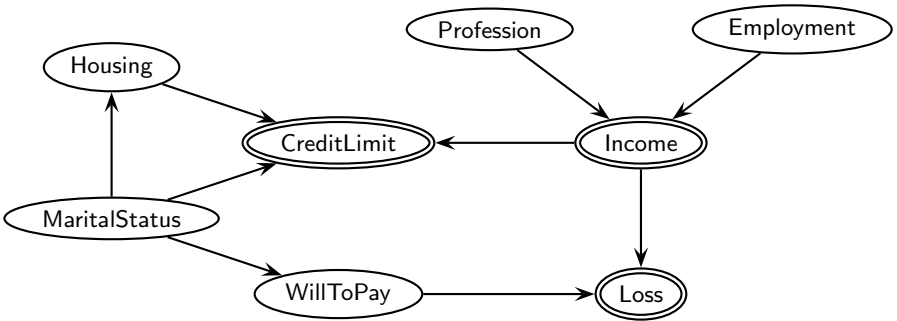
The qualitative and quantitative specifications complete the specification of  $\mathcal{N}$ . The joint distribution induced by  $\mathcal{N}$  is

$$\begin{aligned}P(X_1 = \text{false}) * p(X_2, X_3) &= 0.75 * \mathcal{N}\left(\begin{pmatrix} 0 \\ -5 \end{pmatrix}, \begin{pmatrix} 1 & 10 \\ 10 & 5.1 \end{pmatrix}\right), \\ P(X_1 = \text{true}) * p(X_2, X_3) &= 0.25 * \mathcal{N}\left(\begin{pmatrix} 0 \\ 5 \end{pmatrix}, \begin{pmatrix} 1 & 10 \\ 10 & 5.2 \end{pmatrix}\right).\end{aligned}$$

Determining the joint distribution induced by  $\mathcal{N}$  requires a series of non-trivial computations. We refer the reader to the next chapter for a brief treatment of inference in CLG Bayesian networks. A detailed treatment of these computations is beyond the scope of this book.

*Example 4.4 (Adapted from Lauritzen (1992a)).* Consider a banker who is monitoring her clients in order to limit future loss from each client account. The task of the banker is to identify clients who may have problems repaying their loans by predicting potential future loss originating from each individual customer based on demographic information and credit limit.

Figure 4.4 shows a simple CLG Bayesian network model for this scenario. **Loss** is a linear function of variables **Income** (**I**) given variable **WillToPay** (**W**). **CreditLimit** (**C**) is a linear function of **Income** given **Housing** (**H**) and **MaritalStatus** (**M**). In addition **MaritalStatus** is also a causal factor of **Housing** and **WillToPay**, while **Profession** and **Employment** are causal factors of **Income**.



**Fig. 4.4.** CLG Bayesian network for credit account management.

With the model, the banker may enter observations on each client and compute an expected loss for that client. The model may be extended to

include various risk indicators and controls in order to facilitate a scenario-based analysis on each client.

The reason for restricting our attention to the case of conditional linear Gaussian distributions is that only for this case is exact probabilistic inference feasible by local computations. For most other cases it is necessary to resort to approximate reasoning.

## 4.2 Decision Making Under Uncertainty

The framework of influence diagrams (Howard & Matheson 1981) is an effective modeling framework for representation and analysis of (Bayesian) decision making under uncertainty. Influence diagrams provide a natural representation for capturing the semantics of decision making with a minimum of clutter and confusion for the decision maker (Shachter & Peot 1992). Solving a decision problem amounts to (i) determining an optimal strategy that maximizes the expected utility for the decision maker and (ii) computing the maximal expected utility of adhering to this strategy.

An influence diagram is a type of causal model that differs from a Bayesian network. A Bayesian network is a probabilistic network for reasoning under uncertainty, whereas an influence diagram is a probabilistic network for reasoning about decision making under uncertainty. An influence diagram is a graphical representation of a decision problem involving a sequence of interleaved decisions and observations. Similar to Bayesian networks, an influence diagram is a compact and intuitive probabilistic knowledge representation (a probabilistic network). It consists of a graphical representation describing dependence relations between entities of a problem domain, points in time where decisions are to be made, and a precedence ordering specifying the order on decisions and observations. It also consists of a quantification of the strengths of the dependence relations and the preferences of the decision maker. As such, an influence diagram can be considered as a Bayesian network augmented with decision variables, utility functions specifying the preferences of the decision maker, and a precedence ordering.

As decision makers we are interested in making the best possible decisions given our model of the problem domain. Therefore, we associate utilities with state configurations of the network. These utilities are represented by *utility functions* (also known as *value functions*). Each utility function associates a utility value with each configuration of its domain variables. The objective of decision analysis is to identify the decision options that produce the highest expected utility.

By making decisions, we influence the probabilities of the configurations of the network. To identify the decision option with the highest expected utility, we compute the expected utility of each decision alternative. If  $A$  is a decision variable with options  $a_1, \dots, a_m$ ,  $H$  is a hypothesis with states  $h_1, \dots, h_n$ ,



and  $\varepsilon$  is a set of observations in the form of evidence, then we can compute the utility of each outcome of the hypothesis and the expected utility of each action. The utility of an outcome  $(\mathbf{a}_i, \mathbf{h}_j)$  is  $U(\mathbf{a}_i, \mathbf{h}_j)$  where  $U(\cdot)$  is our utility function. The expected utility of performing action  $\mathbf{a}_i$  is

$$EU(\mathbf{a}_i) = \sum_j U(\mathbf{a}_i, \mathbf{h}_j)P(\mathbf{h}_j | \varepsilon),$$

where  $P(\cdot)$  represents our belief in  $H$  given  $\varepsilon$ . The utility function  $U(\cdot)$  encodes the preferences of the decision maker on a numerical scale.

We shall choose the alternative with the highest expected utility; this is known as the maximum expected utility principle. Choosing the action, which maximizes the expected utility amounts to selecting an option  $\mathbf{a}^*$  such that

$$\mathbf{a}^* = \arg \max_{\mathbf{a} \in A} EU(\mathbf{a}).$$

There is an important difference between observations and actions. An observation of an event is passive in the sense that we assume that an observation does not effect the state of the world whereas the decision on an action is active in the sense that an action enforces a certain event. The event enforced by a decision may or may not be included in the model depending on whether or not the event is relevant for the reasoning. If the event enforced by an action  $A$  is represented in our model, then  $A$  is referred to as an intervening action, otherwise it is referred to as a non-intervening action.

#### 4.2.1 Discrete Influence Diagrams

A (discrete) influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  is a four-tuple consisting of a set,  $\mathcal{X}$ , of discrete random variables and discrete decision variables, an acyclic, directed graph  $\mathcal{G}$ , a set of conditional probability distributions  $\mathcal{P}$ , and a set of utility functions  $\mathcal{U}$ . The acyclic, directed graph,  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ , contains nodes representing random variables, decision variables, and utility functions (also known as value or utility nodes).

Each decision variable,  $D$ , represents a specific point in time under the model of the problem domain where the decision maker has to make a decision. The decision options or alternatives are the states  $(d_1, \dots, d_n)$  of  $D$  where  $n = \|D\|$ . The decision options are mutually exclusive and exhaustive. The usefulness of each decision option is measured by the local utility functions associated with  $D$  or one of its descendants in  $\mathcal{G}$ . Each local utility function  $u(X_{pa(v)}) \in \mathcal{U}$ , where  $v \in \mathcal{V}_U$  is a utility node, represents an additive contribution to the total utility function  $u(\mathcal{X})$  in  $\mathcal{N}$ . Thus, the total utility function is the sum of all the utility functions in the influence diagram, i.e.,  $u(\mathcal{X}) = \sum_{v \in \mathcal{V}_U} u(X_{pa(v)})$ .

**Definition 4.4.** A (discrete) influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  consists of

- a DAG  $\mathcal{G} = (V, E)$  with nodes,  $V$ , and directed links,  $E$ , encoding dependence relations and information precedence including a total order on decisions
- a set of discrete random variables,  $\mathcal{X}_C$ , and discrete decision variables,  $\mathcal{X}_D$ , such that  $\mathcal{X} = \mathcal{X}_C \cup \mathcal{X}_D$  represented by nodes of  $\mathcal{G}$
- a set of conditional probability distributions,  $\mathcal{P}$ , containing one distribution,  $P(X_v | X_{pa(v)})$ , for each discrete random variable  $X_v$
- a set of utility functions,  $\mathcal{U}$ , containing one utility function,  $u(X_{pa(v)})$ , for each node  $v$  in the subset  $V_U \subset V$  of utility nodes.

An influence diagram supports the representation and solution of sequential decision problems with multiple local utility functions under the *no-forgetting assumption* (Howard & Matheson 1981) (i.e., perfect recall is assumed of all observations and decisions made in the past).

An influence diagram,  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$ , should be constructed such that one can determine exactly which variables are known prior to making each decision. If the state of a variable  $X_v \in \mathcal{X}_C$  will be known at the time of making a decision  $D_w \in \mathcal{X}_D$ , this will (probably) have an impact on the choice of alternative at  $D$ . An observation on  $X_v$  made prior to decision  $D_w$  is represented in  $\mathcal{N}$  by making  $v$  a parent of  $w$  in  $\mathcal{G}$ . If  $v$  is a parent of  $w$  in  $\mathcal{G} = (V, E)$  (i.e.,  $(v, w) \in E$ , implying  $X_v \in X_{pa(w)}$ ), then it is assumed that  $X_v$  is observed prior to making the decision represented by  $D_w$ . The link  $(v, w)$  is then referred to as an *informational link*.

In an influence diagram there must also be a total order on the decision variables  $\mathcal{X}_D = \{D_1, \dots, D_n\} \subseteq \mathcal{X}$ . That is, there can be only one sequence in which the decisions are made. We add informational links to specify a total order  $(D_1, \dots, D_n)$  on  $\mathcal{X}_D = \{D_1, \dots, D_n\}$ . There need only be a directed path from one decision variable to the next one in the decision sequence in order to enforce a total order on the decisions.

In short, a link,  $(w, v)$ , into a node representing a random variable,  $X_v$ , denotes a possible probabilistic dependence relation of  $X_v$  on  $Y_w$  while a link from a node representing a variable,  $X$ , into a node representing a decision variable,  $D$ , denotes that the state of  $X$  is known when decision  $D$  is to be made. A link,  $(w, v)$ , into a node representing a local utility function,  $u$ , denotes functional dependence of  $u$  on  $X_v \in \mathcal{X}$ .

The chain rule of influence diagrams is

$$EU(\mathcal{X}) = \prod_{X_v \in \mathcal{X}_C} P(X_v | X_{pa(v)}) \sum_{w \in V_U} u(X_{pa(w)}).$$

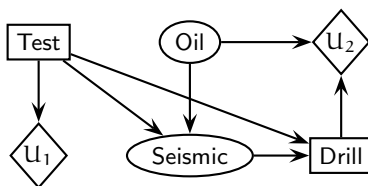
An influence diagram is a compact representation of a joint expected utility function.

In the graphical representation of an influence diagram, utility functions are represented by rhombuses (diamond-shaped nodes), whereas decision variables are represented as rectangles.

*Example 4.5 (Oil Wildcatter (Raiffa 1968)).* Consider the fictitious example of an oil wildcatter about to decide whether or not to drill for oil at a specific site. The situation of the oil wildcatter is the following.

An oil wildcatter must decide either to *drill* or *not to drill*. He is uncertain whether the *hole* will be dry, wet, or soaking. The wildcatter could *take seismic soundings* that will help determine the *geological structure* of the site. The soundings will give a closed reflection pattern (indication of much oil), an open pattern (indication of some oil), or a diffuse pattern (almost no hope of oil).

The qualitative domain knowledge extracted from the above description can be formulated as the DAG shown in Figure 4.5. The state spaces of the variables are as follows  $\text{dom}(\text{Drill}) = \{\text{no}, \text{yes}\}$ ,  $\text{dom}(\text{Oil}) = \{\text{dry}, \text{wet}, \text{soaking}\}$ ,  $\text{dom}(\text{Seismic}) = \{\text{closed}, \text{open}, \text{diffuse}\}$ , and  $\text{dom}(\text{Test}) = \{\text{no}, \text{yes}\}$ .



**Fig. 4.5.** The Oil Wildcatter network.

Figure 4.5 shows how the qualitative knowledge of the example can be compactly specified in the structure of an influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$ .

The quantitative probabilistic knowledge as defined by the structure of  $\mathcal{G}$  consists of  $P(\text{Oil})$  and  $P(\text{Seismic}|\text{Oil}, \text{Test})$ , while the quantitative utility knowledge consists of  $U_1(\text{Test})$  and  $U_2(\text{Drill}, \text{Oil})$ .

The cost of testing is 10k whereas the cost of drilling is 70k. The utility of drilling is 0k, 120k, and 270k for a dry, wet, and soaking hole, respectively. Hence,  $U_1(\text{Test}) = (0, -10)$  and  $U_2(\text{Drill} = \text{yes}, \text{Oil}) = (-70, 50, 200)$ . The test result *Seismic* depends on the amount of oil *Oil* as specified in Table 4.5. The prior belief of the oil wildcatter on the amount of oil at the site is  $P(\text{Oil}) = (0.5, 0.3, 0.2)$ .

Oil	Seismic		
	diffuse	open	closed
dry	0.6	0.3	0.1
wet	0.3	0.4	0.3
soaking	0.1	0.4	0.5

**Table 4.5.** The conditional probability distribution  $P(\text{Seismic}|\text{Oil}, \text{Test} = \text{yes})$ .

This produces a completely specified influence diagram representation of the oil wildcatter decision problem. The decision strategy of the oil wildcatter will be considered in Example 4.7 on the facing page.

As a consequence of the total order on decisions and the set of informational links, the set of discrete random variables and decision variables are subjected to a partial ordering. The random variables are partitioned into disjoint *information sets*  $\mathcal{J}_0, \dots, \mathcal{J}_n$  (i.e.,  $\mathcal{J}_i \cap \mathcal{J}_j = \emptyset$  for  $i \neq j$ ) relative to the decision variables specifying the precedence order. The information set  $\mathcal{J}_i$  is the set of variables observed after decision  $D_i$  and before decision  $D_{i+1}$ . The partition induces a partial ordering,  $\prec$ , on the variables  $\mathcal{X}$ . The set of variables observed between decisions  $D_i$  and  $D_{i+1}$  precedes  $D_{i+1}$  and succeeds  $D_i$  in the ordering

$$\mathcal{J}_0 \prec D_1 \prec \mathcal{J}_1 \prec \dots \prec D_n \prec \mathcal{J}_n,$$

where  $\mathcal{J}_0$  is the set of discrete random variables observed before the first decision,  $\mathcal{J}_i$  is the set of discrete random variables observed after making decision  $D_i$  and before making decision  $D_{i+1}$ , for all  $i = 1, \dots, n-1$ , and  $\mathcal{J}_n$  is the set of discrete random variables never observed or observed after the last decision  $D_n$  has been made. If the influence diagram is not constructed or used according to this constraint, the computed expected utilities will (of course) not be correct.

*Example 4.6.* The total order on decisions and the informational links of Example 4.5 on the previous page induce the following partial order:

$$\{\} \prec \text{Test} \prec \{\text{Seismic}\} \prec \text{Drill} \prec \{\text{Oil}\}.$$

This partial order turns out to be a total order. In general, this is not the case. The total order specifies the flow of information in the decision problem. No observations are made prior to the decision on whether or not to **Test**. After testing and before deciding on whether or not to **Drill**, the oil wildcatter will make an observation on **Seismic**, i.e. the test result is available before the **Drill** decision. After drilling **Oil** is observed.

To solve an influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  with decision variables,  $\mathcal{X}_D$ , is to identify an optimal strategy,  $\hat{\Delta}$ , over  $\mathcal{X}_D$  maximizing the expected utility for the decision maker and to compute the *maximum expected utility*  $\text{MEU}(\hat{\Delta})$  of  $\hat{\Delta}$ . A *strategy*,  $\Delta$ , is an ordered set of decision policies  $\Delta = (\delta_1, \dots, \delta_n)$  including one decision policy for each decision  $D \in \mathcal{X}_D$ . An *optimal strategy*  $\hat{\Delta} = (\hat{\delta}_1, \dots, \hat{\delta}_n)$ , maximizes the expected utility over all possible strategies, i.e., it satisfies

$$\text{EU}(\hat{\Delta}) \geq \text{EU}(\Delta),$$

for all strategies  $\Delta$ .

The *decision history* of  $D_i$ , denoted  $\mathcal{H}(D_i)$ , is the set of previous decisions and their parent variables

$$\mathcal{H}(\mathbf{D}_i) = \bigcup_{j=1}^{i-1} (\{\mathbf{D}_j\} \cup \mathbf{X}_{\text{pa}(\mathbf{v}_j)}) = \{\mathbf{D}_1, \dots, \mathbf{D}_{i-1}\} \cup \bigcup_{j=0}^{i-2} \mathcal{J}_j,$$

where  $\mathbf{v}_j$  denotes the node that represents  $\mathbf{D}_j$ .

The *decision past* of  $\mathbf{D}_i$ , denoted  $\mathcal{J}(\mathbf{D}_i)$ , is the set of its parent variables and the decision history  $\mathcal{H}(\mathbf{D}_i)$

$$\begin{aligned} \mathcal{J}(\mathbf{D}_i) &= \mathbf{X}_{\text{pa}(\mathbf{v}_i)} \cup \mathcal{H}(\mathbf{D}_i) \\ &= \mathbf{X}_{\text{pa}(\mathbf{v}_i)} \cup \bigcup_{j=1}^{i-1} (\{\mathbf{D}_j\} \cup \mathbf{X}_{\text{pa}(\mathbf{v}_j)}) \\ &= \{\mathbf{D}_1, \dots, \mathbf{D}_{i-1}\} \cup \bigcup_{j=1}^{i-1} \mathcal{J}_j. \end{aligned}$$

Hence,  $\mathcal{J}(\mathbf{D}_i) \setminus \mathcal{H}(\mathbf{D}_i) = \mathcal{J}_{i-1}$  are the variables observed between  $\mathbf{D}_{i-1}$  and  $\mathbf{D}_i$ .

The *decision future* of  $\mathbf{D}_i$ , denoted  $\mathcal{F}(\mathbf{D}_i)$  is the set of its descendant variables

$$\begin{aligned} \mathcal{F}(\mathbf{D}_i) &= \mathcal{J}_i \cup \left( \bigcup_{j=i+1}^n (\{\mathbf{D}_j\} \cup \mathbf{X}_{\text{pa}(\mathbf{v}_j)}) \right) \\ &= \{\mathbf{D}_{i+1}, \dots, \mathbf{D}_n\} \cup \bigcup_{j=i}^n \mathcal{J}_j. \end{aligned}$$

A *policy*  $\delta_i$  is a mapping from the information set  $\mathcal{J}(\mathbf{D}_i)$  of  $\mathbf{D}_i$  to the state space  $\text{dom}(\mathbf{D}_i)$  of  $\mathbf{D}_i$  such that  $\delta_i : \mathcal{J}(\mathbf{D}_i) \rightarrow \text{dom}(\mathbf{D}_i)$ . A policy for decision  $\mathbf{D}$  specifies the optimal action for the decision maker for all possible observations made prior to making decision  $\mathbf{D}$ .

It is only necessary to consider  $\delta_i$  as a function from relevant observations on  $\mathcal{J}(\mathbf{D}_i)$  to  $\text{dom}(\mathbf{D}_i)$ , i.e., observations with an unblocked path to a utility descendant of  $\mathbf{D}_i$ . Relevance of an observation with respect to a decision is defined in Section 4.2.3 on page 89.

*Example 4.7.* After solving the influence diagram, we obtain an optimal strategy  $\hat{\Delta} = \{\hat{\delta}_{\text{Test}}, \hat{\delta}_{\text{Drill}}\}$ . Hence, the optimal strategy  $\hat{\Delta}$  (we show how to identify the optimal strategy for this example in Example 5.11 on page 126) consists of a policy  $\hat{\delta}_{\text{Test}}$  for Test and a policy  $\hat{\delta}_{\text{Drill}}$  for Drill given Test and Seismic

$$\hat{\delta}_{\text{Test}} = \text{yes}$$

$$\hat{\delta}_{\text{Drill}}(\text{Seismic}, \text{Test}) = \begin{cases} \text{yes} & \text{Seismic} = \text{closed}, \text{Test} = \text{no} \\ \text{yes} & \text{Seismic} = \text{open}, \text{Test} = \text{no} \\ \text{yes} & \text{Seismic} = \text{diffuse}, \text{Test} = \text{no} \\ \text{yes} & \text{Seismic} = \text{closed}, \text{Test} = \text{yes} \\ \text{yes} & \text{Seismic} = \text{open}, \text{Test} = \text{yes} \\ \text{no} & \text{Seismic} = \text{diffuse}, \text{Test} = \text{yes} \end{cases}$$

The policy for **Test** says that we should always test, while the policy for **Drill** says that we should drill except when the test produces a diffuse pattern indicating almost no hope of oil.

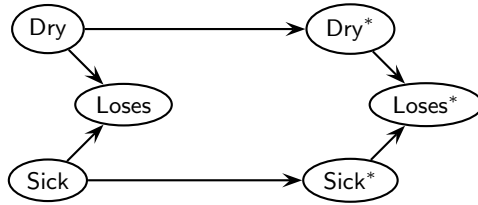
An intervening decision **D** of an influence diagram is a decision that may impact the value of another variable **X** represented in the model. In order for **D** to potentially impact the value of **X**, **X** must be a descendant of **D** in **G**. This can be realized by considering the d-separation criterion (consider the information blocking properties of the converging connection) and the set of evidence available when making the decision **D**. Consider, for instance, the influence diagram shown in Figure 4.5. The decision **Test** is an intervening decision as it impacts the value of **Seismic**. It cannot, however, impact the value of **Oil** as **Oil** is a non-descendant of **Test** and we have no *down-stream* evidence when making the decision on **Test**. Since decision **D** may only have a potential impact on its descendants, the usefulness of **D** can only be measured by the utility descendants of **D**.

A total ordering on the decision variables is usually assumed. This assumption can, however, be relaxed. Nielsen & Jensen (1999) describe when decision problems with only a partial ordering on the decision variables are *well-defined*. In addition, the limited memory influence diagram (Lauritzen & Nilsson 2001) and the unconstrained influence diagram (Vomlelová & Jensen 2002) support the use of unordered decision variables.

*Example 4.8 (Apple Jack).* We consider once again the problems of Apple Jack from Example 4.1 on page 66. A Bayesian network for reasoning about the causes of the apple tree losing its leaves was shown in Figure 4.1 on page 66.

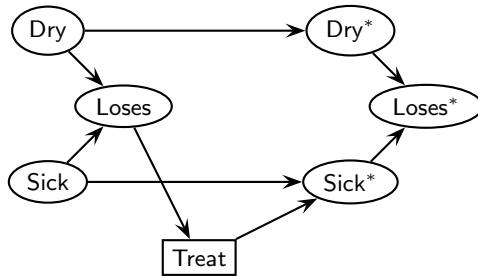
We continue the example by assuming that Apple Jack wants to decide whether or not to invest resources in giving the tree some treatment against a possible disease. Since this involves a decision through time, we have to extend the Bayesian network to capture the impact of the treatment on the development of the disease. We first add three variables similar to those already in the network. The new variables **Sick\***, **Dry\***, and **Loses\*** correspond to the original variables, except that they represent the situation at the time of harvest. These variables have been added in Figure 4.6 on the facing page.

The additional variables have the same states as the original variables: **Sick\***, **Dry\***, and **Loses\*** all have states **no** and **yes**. In the extended model, we



**Fig. 4.6.** We model the system at two different points in time (before and after a decision) by replicating the structure.

expect a causal influence from the original **Sick** variable on the **Sick\*** variable and from the original **Dry** variable on the **Dry\*** variable. The reason is the following. If, for example, we expect the tree to be sick now, then this is also very likely to be the case in the future and especially at the time of harvest. Of course, the strength of the influence depends on how far out in the future we look. Perhaps one could also have a causal influence from **Loses** on **Loses\***, but we have chosen not to model such a possible dependence relation in this model.



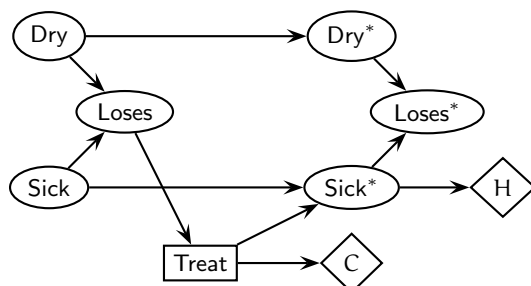
**Fig. 4.7.** Addition of a decision variable for treatment to the Bayesian network in Figure 4.6.

Apple Jack may try to heal the tree with a treatment to get rid of the possible disease. If he expects that the loss of leaves is caused by drought, he might save his money and just wait for rain. The action of giving the tree a treatment is now added as a decision variable to the Bayesian network, which will then no longer be a Bayesian network. Instead it becomes the influence diagram shown in Figure 4.7.

The **treat** decision variable has the states **no** and **yes**. There is a causal link (**Treat**, **Sick\***) from the decision **Treat** to **Sick\*** as we expect the treatment to have a causal impact on the future health of the tree. There is an

informational link from **Loses** to **Treat** as we expect Apple Jack to observe whether or not the apple tree is losing its leaves prior to making the decision on treatment.

We need to specify the utility functions enabling us to compute the expected utility of the decision options. This is done by adding utility functions to the influence diagram. Each utility function will represent a term of an additively decomposing utility function and each term will contribute to the total utility. The utility functions are shown in Figure 4.8.



**Fig. 4.8.** A complete qualitative representation of the influence diagram used for decision making in Apple Jack’s orchard.

The utility function **C** specifies the cost of the treatment while utility function **H** specifies the gain of the harvest. The latter depends on the state of **Sick\***, indicating that the production of apples depends on the health of the tree.

Treat	Sick	Sick*	
		no	yes
no	no	0.98	0.02
no	yes	0.01	0.99
yes	no	0.99	0.01
yes	yes	0.8	0.2

**Table 4.6.** The conditional probability distribution  $P(\text{Sick}^*|\text{Treat},\text{Sick})$ .

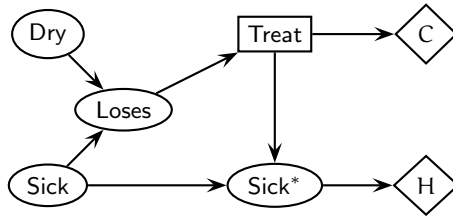
Figure 4.8 shows the complete qualitative representation of the influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$ . To complete the quantitative representation as well, we need to specify the conditional probability distributions,  $\mathcal{P}$ , and utility functions,  $\mathcal{U}$ , of  $\mathcal{N}$ . Recall that a decision variable does not have any distribution. The appropriate probability distributions are specified in Tables 4.6–4.8.



Dry	Dry*	
	no	yes
no	0.95	0.05
yes	0.4	0.6

**Table 4.7.** The conditional probability distribution  $P(\text{Dry}^* | \text{Dry})$ .

If we have a healthy tree ( $\text{Sick}^*$  is in state no), then Apple Jack will get an income of €200, while if the tree is sick ( $\text{Sick}^*$  is in state yes) his income is only €30, i.e.,  $H(\text{Sick}^*) = (200, 30)$ . To treat the tree, he has to spend €80, i.e.,  $C(\text{Treat}) = (0, -80)$ .



**Fig. 4.9.** A simplified influence diagram for the decision problem of Apple Jack.

Since  $\text{Dry}^*$  and  $\text{Loses}^*$  are not relevant for the decision on whether or not to treat and since we do not care about their distribution, we remove them from our model producing the final model shown in Figure 4.9. Variables  $\text{Dry}^*$  and  $\text{Loses}^*$  are in fact barren variables, see Section 3.3.4 on page 49. In an influence diagram a variable is a barren variable when none of its descendants are utility nodes and none of its descendants are ever observed.

Dry*	Sick*	Loses*	
		no	yes
no	no	0.98	0.02
no	yes	0.1	0.9
yes	no	0.15	0.85
yes	yes	0.05	0.95

**Table 4.8.** The conditional probability distribution  $P(\text{Loses}^* | \text{Dry}^*, \text{Sick}^*)$ .

The purpose of our influence diagram is to be able to determine the optimal strategy for Apple Jack. After solving  $\mathcal{N}$ , we obtain the following policy  $(\delta_{\text{Treat}} : \text{Loses} \rightarrow \text{dom}(\text{Treat}))$  for Treat

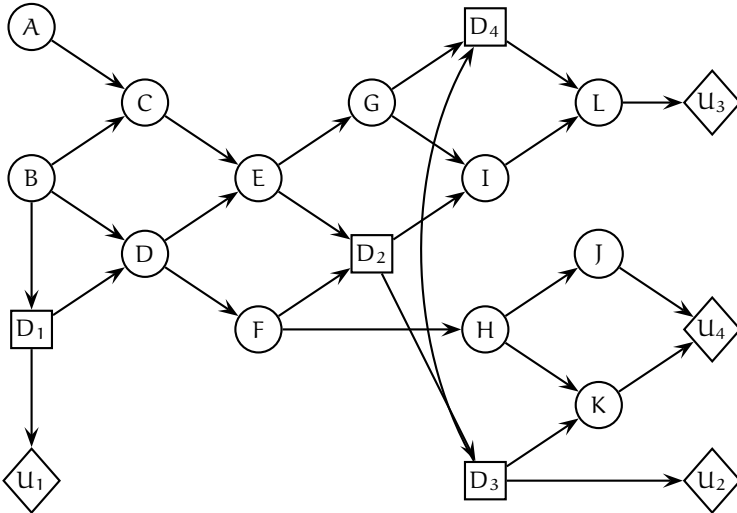
$$\delta_{\text{Treat}}(\text{Loses}) = \begin{cases} \text{no} & \text{Loses} = \text{no} \\ \text{yes} & \text{Loses} = \text{yes} \end{cases}$$

Hence, we should only treat the tree when it loses its leaves. In Section 5.2, we describe how to solve an influence diagram.

Notice that since a policy is a mapping from all possible observations to decision options, it is sufficient to solve an influence diagram once. Hence, the computed strategy can be used by the decision maker each time she or he is faced with the decision problem.

### Implications of Perfect Recall

As mentioned above, when using influence diagrams to represent decision problems we assume perfect recall. This assumption states that at the time of any decision, the decision maker remembers all past decisions and all previously known information (as enforced by the informational links). This implies that a decision variable and all of its parent variables are informational parents of all subsequent decision variables. Due to this assumption it is not necessary to include no-forgetting links in the DAG of the influence diagram as they — if missing — will implicitly be assumed present.



**Fig. 4.10.** An influence diagram representing the sequence of decisions  $D_1, D_2, D_3, D_4$ .

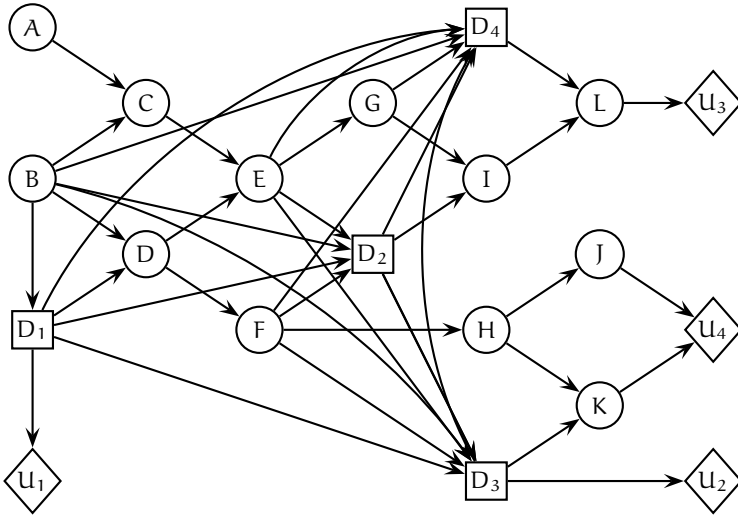
*Example 4.9.* (Jensen, Jensen & Dittmer 1994) Let  $\mathcal{N}$  be the influence diagram in Figure 4.10 on the preceding page. This influence diagram represents a decision problem involving four decisions  $D_1$ ,  $D_2$ ,  $D_3$ , and  $D_4$  in that order.

From the structure of  $\mathcal{N}$ , the following partial ordering on the random and decision variables can be read

$$\{B\} \prec D_1 \prec \{E, F\} \prec D_2 \prec \{\} \prec D_3 \prec \{G\} \prec D_4 \prec \{A, C, D, H, I, J, K, L\}.$$

This partial ordering specifies the flow of information in the decision problem represented by  $\mathcal{N}$ . Thus, the initial (relevant) information available to the decision maker is an observation of  $B$ . After making a decision on  $D_1$ , the decision maker observes  $E$  and  $F$ . After the observations of  $E$  and  $F$  a decision on  $D_2$  is made, and so on.

Notice that no-forgetting links have been left out, e.g., there are no links from  $B$  to  $D_2$ ,  $D_3$ , or  $D_4$ . These links are included in Figure 4.11. The difference in complexity of reading the graph is apparent.



**Fig. 4.11.** The influence diagram of Figure 4.10 with no-forgetting links.

As this example shows, a rather informative analysis can be performed by reading only the structure of the graph of  $\mathcal{N}$ .

#### 4.2.2 Conditional LQG Influence Diagrams

Conditional linear-quadratic Gaussian influence diagrams combine conditional linear Gaussian Bayesian networks, discrete influence diagrams, and quadratic

utility functions into a single framework supporting decision making under uncertainty with both continuous and discrete variables (Madsen & Jensen 2005).

**Definition 4.5.** A CLQG influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{F}, \mathcal{U})$  consists of

- a DAG  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with nodes,  $\mathcal{V}$ , and directed links,  $\mathcal{E}$ , encoding dependence relations and information precedence including a total order on decisions
- a set of random variables,  $\mathcal{X}_{\mathcal{C}}$ , and decision variables,  $\mathcal{X}_{\mathcal{D}}$ , such that  $\mathcal{X} = \mathcal{X}_{\mathcal{C}} \cup \mathcal{X}_{\mathcal{D}}$  represented by nodes of  $\mathcal{G}$
- a set of conditional probability distributions,  $\mathcal{P}$ , containing one distribution,  $P(X_v | X_{\text{pa}(v)})$ , for each discrete random variable  $X_v$
- a set of conditional linear Gaussian probability density functions,  $\mathcal{F}$ , containing one density function,  $p(Y_w | X_{\text{pa}(w)})$ , for each continuous random variable  $Y_w$
- a set of linear-quadratic utility functions,  $\mathcal{U}$ , containing one utility function,  $u(X_{\text{pa}(v)})$ , for each node  $v$  in the subset  $\mathcal{V}_{\mathcal{U}} \subset \mathcal{V}$  of utility nodes.

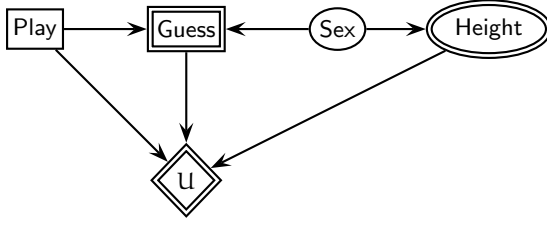
We refer to a conditional linear-quadratic Gaussian influence diagram as a CLQG influence diagram. The chain rule of CLQG influence diagrams is

$$\begin{aligned}
 \text{EU}(\mathcal{X}_{\Delta} = \mathbf{i}, \mathcal{X}_{\Gamma}) &= P(\mathcal{X}_{\Delta} = \mathbf{i}) * \mathbb{N}_{|\mathcal{X}_{\Gamma}|}(\boldsymbol{\mu}(\mathbf{i}), \boldsymbol{\sigma}^2(\mathbf{i})) * \sum_{z \in \mathcal{V}_{\mathcal{U}}} u(X_{\text{pa}(z)}) \\
 &= \prod_{v \in \mathcal{V}_{\Delta}} P(i_v | i_{\text{pa}(v)}) * \prod_{w \in \mathcal{V}_{\Gamma}} p(y_w | X_{\text{pa}(w)}) * \\
 &\quad \sum_{z \in \mathcal{V}_{\mathcal{U}}} u(X_{\text{pa}(z)}),
 \end{aligned}$$

for each configuration  $\mathbf{i}$  of  $\mathcal{X}_{\Delta}$ .

Recall that in the graphical representation of a CLQG influence diagram, continuous utility functions are represented by double rhombuses and continuous decision variables as double rectangles.

A CLQG influence diagram is a compact representation of a joint expected utility function over continuous and discrete variables, where continuous variables are assumed to follow a linear Gaussian distribution conditional on a subset of discrete variables while utility functions are assumed to be linear-quadratic in the continuous variables (and constant in the discrete). This may seem a severe assumption which could be limiting to the usefulness of the CLQG influence diagram. The assumption seems to indicate that all local utility functions specified in a CLQG influence diagram should be linear-quadratic in the continuous variables. This is not the case, however, as the following examples show. We will consider the assumption in more detail in Section 5.2 on solving decision models.



**Fig. 4.12.** A CLQG influence diagram for a simple guessing game.

*Example 4.10 (Guessing Game (Madsen & Jensen 2005)).* Figure 4.12 illustrates a CLQG influence diagram,  $\mathcal{N}$ , representation of a simple guessing game with two decisions.

The first decision, represented by the discrete decision variable **Play** with states **reward** and **play**, is to either accept an immediate reward or to play a game where you will receive a payoff determined by how good you are at guessing the height of a person, represented by the continuous random variable **Height**, based on knowledge about the sex of the person, represented by the discrete random variable **Sex** with states **female** and **male**. The second decision, represented by the real-valued decision variable **Guess**, is your guess on the height of the person given knowledge about the sex of the person.

The payoff is a constant (higher than the reward) minus the distance of your guess from the true height of the person measured as height minus guess squared.

To quantify  $\mathcal{N}$ , we need to specify a prior probability distribution for **Sex**, a conditional Gaussian distribution for **Height** and a utility function over **Play**, **Guess**, and **Height**. Assume the prior distribution on **Sex** is  $P(\text{Sex}) = (0.5, 0.5)$  whereas the distribution for **Height** is

$$\mathcal{L}(\text{Height}|\text{female}) = \mathcal{N}(170, 400)$$

$$\mathcal{L}(\text{Height}|\text{male}) = \mathcal{N}(180, 100).$$

We assume the average height of a female to be 170 cm with a standard deviation of 20 cm and average height of a male to be 180 cm with a standard deviation of 10 cm. The utility function over **Play**, **Guess**, **Height** is

$$u(\text{play}, d_2, h) = 150 - (h - d_2)^2$$

$$u(\text{reward}, d_2, h) = 100.$$

We assume the immediate reward is 100. After solving  $\mathcal{N}$ , we obtain an optimal strategy  $\Delta = \{\delta_{\text{Play}}, \delta_{\text{Guess}}\}$

$$\delta_{\text{Play}} = \text{play}$$

$$\delta_{\text{Guess}}(\text{play}, \text{female}) = 170$$

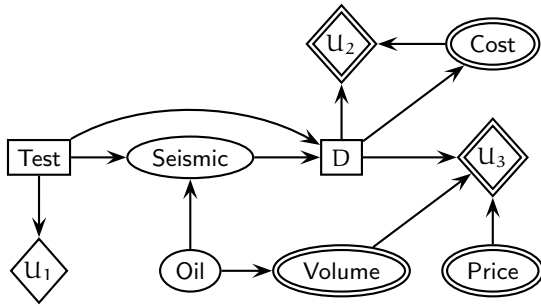
$$\delta_{\text{Guess}}(\text{play}, \text{male}) = 180.$$

The optimal strategy is to guess that the height of a female person is 170 cm and the height of a male person is 180 cm.

In this example the policy for **Guess** reduces to a constant for each configuration of its parent variables. In the general case, the policy for a continuous decision variable is a multi-linear function in its continuous parent variables given the discrete parent variables.

As another example of a CLQG influence diagram consider a revised extension of the Oil Wildcatter problem of Raiffa (1968) (Example 4.5 on page 77). The revised Oil Wildcatter problem, which is further revised here, is due to Cobb & Shenoy (2004).

*Example 4.11 (Oil Wildcatter (Madsen & Jensen 2005)).* The network of the revised version of the Oil Wildcatter problem is shown in Figure 4.13. First, the decision maker makes a decision on whether or not to perform a test **Test** of the geological structure of the site under consideration. When performed, this test will produce a test result, **Seismic** depending on the amount of oil **Oil**. Next, a decision **Drill** on whether or not to drill is made. There is a cost **Cost** associated with drilling, while the revenue is a function of oil volume **Volume** and oil price **Price**.



**Fig. 4.13.** A revised version of the Oil Wildcatter problem.

We assume the continuous random variables (i.e., cost of drilling, oil price, and oil volume) to follow (conditional) Gaussian distributions. The utility function can be stated in thousands of euros as  $U_1(\text{Test} = \text{yes}) = -10$ ,  $U_2(\text{Cost} = c, \text{Drill} = \text{yes}) = -c$ ,  $U_3(\text{Volume} = v, \text{Price} = p, \text{Drill} = \text{yes}) = v * p$ , and zero for the no drill and no test situations.

If the hole is dry, then no oil is extracted:  $\mathcal{L}(\text{Volume} | \text{Oil} = \text{dry}) = \mathcal{N}(0, 0)$ . If the hole is wet, then some oil is extracted:  $\mathcal{L}(\text{Volume} | \text{Oil} = \text{wet}) = \mathcal{N}(6, 1)$ . If the hole is soaking with oil, then a lot of oil is extracted:  $\mathcal{L}(\text{Volume} | \text{Oil} = \text{soaking}) = \mathcal{N}(13.5, 4)$ . The unit is a thousand barrels. The cost of drilling follows a Gaussian distribution  $\mathcal{L}(\text{Cost} | \text{Drill} = \text{yes})$

$= \mathcal{N}(70, 100)$ . We assume that the price of oil Price also follows a Gaussian distribution  $\mathcal{L}(\text{Price}) = \mathcal{N}(20, 4)$ .

Notice that the continuous utility functions  $\mathcal{U}_2$  and  $\mathcal{U}_3$  are not linear-quadratic in their continuous domain variables.

### 4.2.3 Limited Memory Influence Diagrams

The framework of influence diagrams offers compact and intuitive models for reasoning about decision making under uncertainty. Two of the fundamental assumptions of the influence diagram representation are the no-forgetting assumption implying perfect recall of the past and the assumption of a total order on the decisions. The limited memory influence diagram framework (LIMID) (Lauritzen & Nilsson 2001) relaxes both of these fundamental assumptions.

Relaxing the no-forgetting and the total order (on decisions) assumptions largely increases the class of multistage decision problems that can be modeled. LIMIDs allow us to model more types of decision problems than the ordinary influence diagrams.

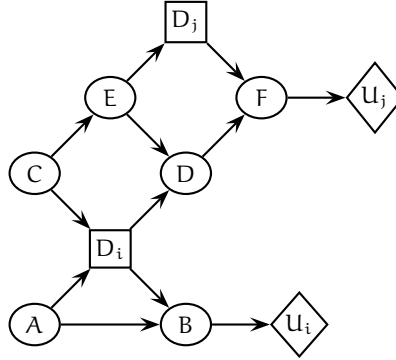
The graphical difference between the LIMID representation and the ordinary influence diagram representation is that the latter representation (as presented in this book) assumes some informational links to be implicitly present in the graph. This assumption is not made in the LIMID representation. For this reason it is necessary to explicitly represent all information available to the decision maker at each decision.

The definition of a limited memory influence diagram is as follows.

**Definition 4.6.** A LIMID  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  consists of

- a DAG  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with nodes  $\mathcal{V}$  and directed links  $\mathcal{E}$  encoding dependence relations and information precedence
- a set of random variables,  $\mathcal{X}_C$ , and discrete decision variables,  $\mathcal{X}_D$ , such that  $\mathcal{X} = \mathcal{X}_C \cup \mathcal{X}_D$  represented by nodes of  $\mathcal{G}$
- a set of conditional probability distributions,  $\mathcal{P}$ , containing one distribution,  $P(X_v | X_{\text{pa}(v)})$ , for each discrete random variable  $X_v$
- a set of utility functions,  $\mathcal{U}$ , containing one utility function,  $u(X_{\text{pa}(v)})$ , for each node  $v$  in the subset  $\mathcal{V}_U \subset \mathcal{V}$  of utility nodes.

Using the LIMID representation it is possible to model multistage decision problems with unordered sequences of decisions and decision problems in which perfect recall cannot be assumed or may not be appropriate. This makes the LIMID framework a good candidate for modeling large and complex domains using an appropriate assumption of forgetfulness of the decision maker. Notice that all decision problems that can be represented as an ordinary influence diagram can also be represented as a LIMID.



**Fig. 4.14.** A LIMID representation of a decision scenario with two unordered decisions.

*Example 4.12.* Figure 4.14 shows an example of a LIMID representation  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  of a decision scenario with two unordered decisions. Prior to decision  $D_i$  observations on the values of  $A$  and  $C$  are made, while prior to decision  $D_j$  an observation on the value of  $E$  is made. Notice that the observations on  $A$  and  $C$  made prior to decision  $D_i$  are not available at decision  $D_j$  and vice versa for the observation on  $E$ .

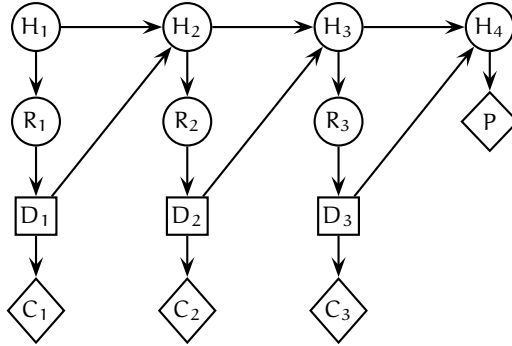
*Example 4.13 (Breeding Pigs (Lauritzen & Nilsson 2001)).* A pig farmer is growing pigs for a period of four months and subsequently selling them. During this period the pigs may or may not develop a certain disease. If a pig has the disease at the time it must be sold for slaughtering, its expected market price is €40. If it is disease free, its expected market price as a breeding animal is €135.

Once a month, a veterinarian inspects each pig and makes a test for presence of the disease. If a pig is ill, the test will indicate this with probability 0.80, and if the pig is healthy, the test will indicate this with probability 0.90. At each monthly visit, the doctor may or may not treat a pig for the disease by injecting a certain drug. The cost of an injection is €13.

A pig has the disease in the first month with probability 0.10. A healthy pig develops the disease in the following month with probability 0.20 without injection, whereas a healthy and treated pig develops the disease with probability 0.10, so the injection has some preventive effect. An untreated pig that is unhealthy will remain so in the following month with probability 0.90, whereas the similar probability is 0.50 for an unhealthy pig that is treated. Thus, spontaneous cure is possible, but treatment is beneficial on average.

The qualitative structure of the LIMID representation of this decision problem is shown in Figure 4.15 on the facing page. Notice that we make the assumption that the test result  $R_i$  is only available for decision  $D_i$ . This





**Fig. 4.15.** Three test-and-treat cycles are performed prior to selling a pig.

implies that the test result is not taken into account for future decisions as it is either forgotten or ignored.

The above example could be modeled as a standard influence diagram, but if more test-and-treat cycles must be performed, the state space size of the past renders decision making intractable. Therefore, it is appropriate to make the decision on whether or not to treat based on the current test result (and not considering past test results and possible treatments) – in this case, individual records for the pigs need not be kept. In short, the example illustrates a situation where instead of keeping track of all past observations and decisions, some of these are deliberately ignored (in order to maintain tractability of the task of computing policies).

### 4.3 Object-Oriented Probabilistic Networks

As large and complex systems are often composed of collections of identical or similar components, models of such systems will naturally contain repetitive patterns. A complex system will typically be composed of a large number of similar or even identical components. This composition of the system should be reflected in models of the system to support model construction, maintenance, and reconfiguration. For instance, a diagnosis model for diagnosing car start problems could reflect the natural decomposition of a car into its engine, electrical system, fuel system, etc.

To support this approach to model development, the framework of object-oriented probabilistic networks has been developed, see e.g. (Koller & Pfeffer 1997, Laskey & Mahoney 1997, Neil, Fenton & Nielsen 2000). Object-orientation may be defined in the following way

$$\text{object-orientation} = \text{objects} + \text{inheritance},$$

where objects are instances of classes and inheritance defines a relationship between classes. Thus, we need to introduce the notion of objects and classes. In this section, we introduce the notion of *object-oriented probabilistic networks (OOPNs)*.

The basic OOPN mechanisms described below support a type of object-oriented specification of probabilistic networks, which makes it simple to reuse models, to encapsulate sub-models (providing a means for hierarchical model specification), and to perform model construction in a top-down fashion, a bottom-up fashion, or a mixture of the two (allowing repeated changes of level of abstraction).

An object-oriented modeling paradigm provides support for working with different levels of abstraction in constructing network models. Repeated changes of focus are partly due to the fact that humans naturally think about systems in terms of hierarchies of abstractions and partly due to lack of ability to mentally capture all details of a complex system simultaneously. Specifying a model in a hierarchical fashion often makes the model less cluttered, and thus provides a better means of communicating ideas among knowledge engineers, domain experts, and users.

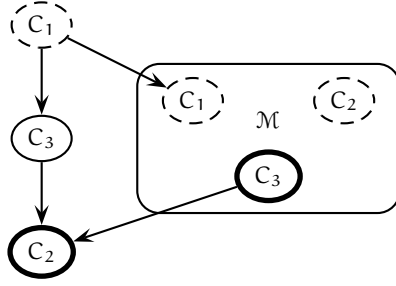
In the OOPN paradigm we present, an *instance* or *object* has a set of variables and related functions (i.e., probability distributions, probability densities, utility functions, and precedence constraints). This implies that in addition to the usual types of nodes, the graph of an OOPN model may contain nodes representing instances of other networks encapsulated in the model. A node that does not represent an instance of a network class is said to represent a *basic* variable.

An instance represents an instantiation of a network class within another network class. A network class is a blueprint for an instance. As such, a *network class* is a named and self-contained description of a probabilistic network, characterized by its name, interface, and hidden part. As instances can be nested, an object-oriented network can be viewed as a hierarchical description of a problem domain. In this way, an instance  $\mathcal{M}$  is the instantiation (or realization) of a network class  $C_{\mathcal{M}}$  within another network class  $C_{\mathcal{N}}$ , see Figure 4.16 on the next page.

An instance connects to other variables via some of its (basic) variables. These variables are known as its *interface* variables. As we wish to support information hiding, the interface variables usually only constitute a subset of the variables in the network class.

Let us be more precise. A network class  $C$  is a DAG over three pairwise disjoint sets of nodes  $\mathcal{I}(C)$ ,  $\mathcal{H}(C)$ ,  $\mathcal{O}(C)$  where  $\mathcal{I}(C)$  are the input nodes,  $\mathcal{H}(C)$  are the hidden nodes, and  $\mathcal{O}(C)$  are the output nodes of  $C$ . The set  $\mathcal{I}(C) \cup \mathcal{O}(C)$  is the interface of  $C$ . Interface nodes may represent either decision or random variables, whereas hidden nodes may be instances of network classes, decision variables, random variables, and utility functions.

**Definition 4.7.** An OOPN network class  $C = (\mathcal{N}, \mathcal{I}, \mathcal{O})$  consists of



**Fig. 4.16.**  $\mathcal{M}$  is an instance of a network class  $C_{\mathcal{M}}$  within another network class  $C_{\mathcal{N}}$ .

- a probabilistic network  $\mathcal{N}$  over variables  $\mathcal{X}$  with DAG  $\mathcal{G}$
- a set of basic variables  $\mathcal{I} \subseteq \mathcal{X}$  specified as input variables and a set of basic variables  $\mathcal{O} \subseteq \mathcal{X}$  specified as output variables such that  $\mathcal{I} \cap \mathcal{O} = \emptyset$  and  $\mathcal{H} = \mathcal{X} \setminus (\mathcal{I} \cup \mathcal{O})$ .

In the graphical representation of an OOPN instances are represented as rectangles with arc-shaped corners whereas input variables are represented as dashed ovals and output variables are represented as bold ovals. If the interface variables of a network instance are not shown, then the instance is collapsed. Otherwise it is expanded.

Since an OOPN implements information hiding through encapsulation, we need to be clear on scope rules. First, we define the notations of simple and qualified names. If  $X$  is a variable of a network instance  $\mathcal{N}$ , then  $X$  is the *simple name* of the variable, whereas  $\mathcal{N}.X$  is the *qualified name* (also known as the long name) of the variable. The scope  $\mathbb{S}(X)$  of a variable  $X$  (i.e., a basic variable or an instance) is defined as the part of a model in which the declaration of  $X$  can be referred to by its simple name.

The (internal) scope  $\mathbb{S}(C)$  of a network class  $C$  is the set of variables and instances which can be referred to by their simple names inside  $C$ . For instance, the internal scope of the network  $C_{\mathcal{N}}$  in Figure 4.16 is  $\mathbb{S}(C_{\mathcal{N}}) = \{C_1, C_3, C_2, \mathcal{M}\}$ . The scope of an instance  $\mathcal{M}$  of a network class  $C_{\mathcal{M}}$ , i.e.,  $\text{class}(\mathcal{M}) = C_{\mathcal{M}}$ , is defined in a similar manner.

The interface variables  $\mathcal{I}(C) \cup \mathcal{O}(C)$  of  $C$  are used to enlarge the visibility of basic variables in the instantiations of  $C$ . The visibility of a variable  $X$  can be enlarged by specifying it as either an input or an output variable of its class.

An input variable  $X$  of an instance  $\mathcal{M}$  is a placeholder for a variable (the parent of  $X$ ) in the encapsulating class of  $\mathcal{M}$ . Therefore, an input variable has at most one parent. An output variable  $X$  of an instance  $\mathcal{M}$ , on the other hand, enlarges the visibility of  $X$  to include the encapsulating network class of  $\mathcal{M}$ .

Notice that the scope of a variable is distinct from visibility of the variable. In Figure 4.16, the scope of output variable  $C_3$  is  $\mathcal{M}$  whereas its visibility is enlarged to include  $\mathcal{N}$  by defining it as an output variable of  $\mathcal{M}$ .

An input variable  $I$  of an instance  $\mathcal{M}$  of network class  $C$  is *bound* if it has a parent  $X$  in the network class encapsulating  $\mathcal{M}$ . Each input random variable  $I$  of a class  $C$  is assigned a default prior probability distribution  $P(I)$ , which becomes the probability distribution of the variable  $I$  in all instances of  $C$  where  $I$  is an unbound input variable. A link into a node representing an input variable may be referred to as a *binding link*.

Let  $\mathcal{M}$  be an instance of network class  $C$ . Each input variable  $I \in \mathcal{I}(C)$  has no parent in  $C$ , no children outside  $C$ , and the corresponding variable of  $\mathcal{M}$  has at most one parent in the encapsulating class of  $\mathcal{M}$ . Each output variable  $O \in \mathcal{O}(C)$  may only have parents in  $\mathcal{I}(C) \cup \mathcal{H}(C)$ . The children and parents of  $H \in \mathcal{H}(C)$  are subsets of the variables of  $C$ .

*Example 4.14.* Figure 4.16 shows a class instance  $\mathcal{M}$  of a network class  $C_{\mathcal{M}}$  instantiated within another network class  $C_{\mathcal{N}}$ . Network class  $C_{\mathcal{N}}$  has input variable  $C_1$ , hidden variables  $C_3$  and  $\mathcal{M}$ , and output variable  $C_2$ . The network class  $C_{\mathcal{M}}$  has input variables  $C_1$  and  $C_2$ , output variable  $C_3$ , and unknown hidden variables. The input variable  $C_1$  of instance  $\mathcal{M}$  is bound to  $C_1$  of  $C_{\mathcal{N}}$  whereas  $C_2$  is unbound.

Since  $C_1 \in \mathcal{I}(C_{\mathcal{N}})$  is bound to  $C_1 \in \mathcal{I}(\mathcal{M})$ , the visibility of  $C_1 \in \mathcal{I}(C_{\mathcal{N}})$  is extended to include the internal scope of  $\mathcal{M}$ . Hence, when we refer to  $C_1 \in \mathcal{I}(C_{\mathcal{M}})$  inside  $C_{\mathcal{M}}$ , we are in fact referring to  $C_1 \in \mathcal{I}(C_{\mathcal{N}})$  as  $C_1 \in \mathcal{I}(C_{\mathcal{M}})$  in instance  $\mathcal{M}$  is a placeholder for  $C_1 \in \mathcal{I}(C_{\mathcal{N}})$  (i.e., you may think of  $C_1 \in \mathcal{I}(C_{\mathcal{M}})$  as the formal parameter of  $C_{\mathcal{M}}$  and  $C_1 \in \mathcal{I}(C_{\mathcal{N}})$  as the actual parameter of  $\mathcal{M}$ ).

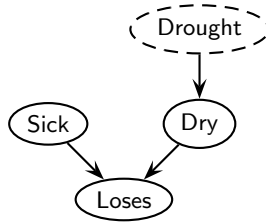
Since an input variable  $I \in \mathcal{I}(\mathcal{M})$  of an instance  $\mathcal{M}$  is a placeholder for a variable  $Y$  in the internal scope of the encapsulating instance of  $\mathcal{M}$ , type checking becomes important when the variable  $Y$  is bound to  $I$ . The variable  $I$  enlarges the visibility of  $Y$  to include the internal scope of  $\mathcal{M}$  and it should therefore be equivalent to  $Y$ . We define two variables  $Y$  and  $X$  to be equivalent as follows.

**Definition 4.8.** *Two variables  $X$  and  $Y$  are equivalent if and only if they are of the same kind, category, and subtype with the same state labels in the case of discrete variables.*

This approach to type checking is referred as *strong type checking*.

If a model contains a lot of repetitive structure, its construction may be tiresome and the resulting model may even be rather cluttered. Both issues are solved when using object-oriented models. Another key feature of object-oriented models is modularity. Modularity allows knowledge engineers to work on different parts of the model independently once an appropriate interface has been defined. The following example will illustrate this point.

*Example 4.15 (Apple Jack's Garden).* Let us assume that Apple Jack from Example 4.1 on page 66 has a garden of three apple trees (including his finest apple tree). He may want to reason about the sickness of each tree given observations on whether or not some of the trees in the garden are losing their leaves.



**Fig. 4.17.** The Apple Tree network class.

Figure 4.17 shows the Apple Tree network class. The prior of each tree being sick will be the same while the dryness of a tree is caused by a drought. The drought is an input variable of the Apple Tree network class. If there is a drought this will impact the dryness of all trees. The prior on drought is  $P(\text{Drought}) = (0.9, 0.1)$  while the conditional distribution of Dry conditional on Drought is shown in Table 4.9.

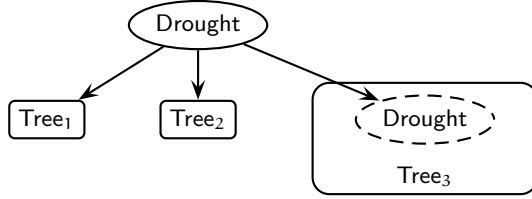
Drought	Dry	
	no	yes
no	0.85	0.15
yes	0.35	0.65

**Table 4.9.** The conditional probability distribution  $P(\text{Drought}|\text{Dry})$ .

Figure 4.18 shows the network class of the Apple Garden. The input variable Drought of each of the instances of the Apple Tree network class is bound to the Drought variable in the Apple Garden network class. This enlarges the visibility of the Drought variable (in the Apple Garden network class) to the internal scope defined by each instance.

The two instances  $\text{Tree}_1$  and  $\text{Tree}_2$  are collapsed (i.e., not showing the interface variables) while the instance  $\text{Tree}_3$  is expanded (i.e., not collapsed) illustrating the interface of the network class.

The Drought variable could be an input variable of the Apple Garden network class as well as it is determined by other complex factors. For the



**Fig. 4.18.** The Apple Garden network consisting of three instantiations of the Apple Tree network.

sake of simplicity of the example, we have made it a hidden variable of the Apple Garden network class.

As mentioned above, a default prior distribution  $P(X)$  is assigned to each input variable  $X \in \mathcal{I}(C)$  of the class  $C = (\mathcal{N}, \mathcal{O}, \mathcal{I})$ . Assigning a default potential to each input variable  $X$  implies that any network class is a valid probabilistic network model.

#### 4.3.1 Chain Rule

It should be clear from the above discussion that each OOPN encodes either a probability distribution or an expected utility function. For simplicity we will discuss only the chain rule for object-oriented (discrete) Bayesian networks. The chain rule of an object-oriented Bayesian network reflects the hierarchical structure of the model.

An instance  $\mathcal{M}$  of network class  $C$  encapsulates a conditional probability distribution over its random variables given its unbound input nodes. For further simplicity, let  $C = (\mathcal{N}, \mathcal{I}, \mathcal{O})$  be a network class over basic discrete random variables only (i.e., no instances, no decisions, and no utilities) with  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  where  $X \in \mathcal{X}$  is the only input variable, i.e.,  $X \in \mathcal{I}$  and  $|\mathcal{I}| = 1$ . Since  $X$  has a default prior distribution,  $\mathcal{N}$  is a valid model representing the joint probability distribution

$$P(\mathcal{X}) = P(X) \prod_{Y_v \neq X} P(Y_v | X_{\text{pa}(v)}).$$

In general, an instance  $\mathcal{M}$  is a representation of the conditional probability distribution  $P(\mathcal{O} | \mathcal{I}')$  where  $\mathcal{I}' \subseteq \mathcal{I}$  is the subset of bound input variables of  $\mathcal{M}$

$$P(\mathcal{O} | \mathcal{I}') = \prod_{X \in \mathcal{I} \setminus \mathcal{I}'} P(X) \prod_{Y_v \notin \mathcal{I}} P(Y_v | X_{\text{pa}(v)}).$$

#### 4.3.2 Unfolded OOPNs

An object-oriented network  $\mathcal{N}$  has an equivalent *flat* or *unfolded* network model representation  $\mathcal{M}$ . The unfolded network model of an object-oriented network  $\mathcal{N}$  is obtained by recursively unfolding the instance nodes of  $\mathcal{N}$ . The

unfolded network representation of a network class is important as it is the structure used for inference.

The joint distribution of an object-oriented Bayesian network model is equivalent to the joint distribution of its unfolded network model

$$P(\mathcal{X}) = \prod_{X_v \in \mathcal{X}_{\mathcal{M}}} P(X_v | X_{\text{pa}(v)}),$$

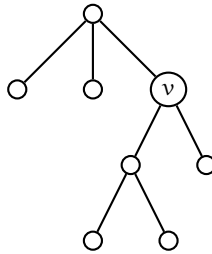
where  $\mathcal{M} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  is the unfolded network.

### 4.3.3 Instance Trees

An object-oriented model is a hierarchical model representation. The *instance tree*  $T$  of an object-oriented model  $\mathcal{N}$  is a tree over the set of instances of classes in  $\mathcal{N}$ . Two nodes  $v_i$  and  $v_j$  in  $T$  (with  $v_i$  closer to the root of  $T$  than  $v_j$ ) are connected by an undirected link if and only if the instance represented by  $v_i$  contains the instance represented by  $v_j$ . The root of an instance tree is the top level network class not instantiated in any other network class within the model. Notice that an instance tree is unique.

In addition to the notion of default potentials there is the notion of the *default instance*. Let  $C$  be a network class with instance tree  $T$ . Each non-root node  $v$  of  $T$  represents an instance of a class  $C_v$  whereas the root node  $r$  of  $T$  represents an instance of the unique class  $C_r$ , which has not been instantiated in any class. This instance is referred to as the default instance of  $C_r$ .

*Example 4.16.* Figure 4.19 shows the instance tree of a network class  $\mathcal{N}$  where the root is the default instance of  $\mathcal{N}$ .



**Fig. 4.19.** An instance tree.

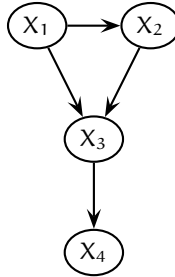
Each node  $v$  of  $T$  represents an instance  $\mathcal{M}$  and the children of  $v$  in  $T$  represents instances in  $\mathcal{M}$ .

#### 4.3.4 Inheritance

Another important concept of the OOPN framework is inheritance. For simplicity, we define inheritance as the ability of an instance to take its interface definition from another instance. Let  $C_1$  be a network class with input variables  $I(C_1)$  and output variables  $O(C_1)$ , i.e.,  $C_1 = (N_1, \mathcal{I}_1, \mathcal{O}_1)$ . A network class  $C_2 = (N_2, \mathcal{I}_2, \mathcal{O}_2)$  may be specified as a subclass of  $C_1$  if and only if  $\mathcal{I}_1 \subseteq \mathcal{I}_2$  and  $\mathcal{O}_1 \subseteq \mathcal{O}_2$ . Hence, subclasses may enlarge the interface.

### 4.4 Dynamic Models

The graph of a probabilistic network is restricted to be a finite acyclic directed graph, see Section 2.1. This seems to imply that probabilistic networks as such do not support models with feedback loops or models of dynamic systems changing over time. This is not the case. A common approach to representing and solving dynamic models or models with feedback loops is to unroll the dynamic model for the desired number of time steps and treat the resulting network as a static network. Similarly, a feedback loop can be unrolled and represented using a desired number of time steps. The unrolled static network is then solved using a standard algorithm applying evidence at the appropriate time steps.



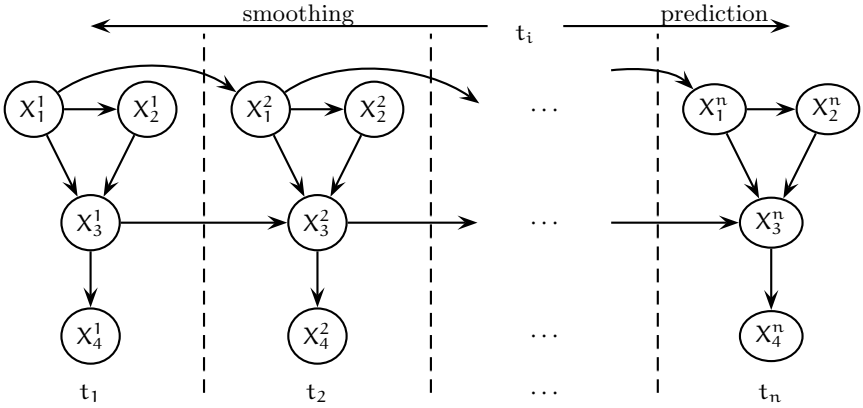
**Fig. 4.20.** The structure of a static network model.

As an example of a dynamic model consider the problem of monitoring the state of a dynamic process over a specific period of time. Assume the network of Figure 4.20 is an appropriate model of the causal relations between variables representing the system at any point in time. The structure of this network is static in the sense that it represents the state of the system at a certain point in time. In the process of monitoring the state of the system over a specific period of time, we will make observations on a subset of the variables in the network and make inference about the remaining unobserved variables.



In addition to reasoning about the current state of the system, we may want to reason about the state of the system at previous and future points in time. For this usage the network in Figure 4.20 is inadequate. Furthermore, the state of the system at the current point in time will impact the state of the system in the future and be impacted by the state of the system in the past.

What is needed is a time-sliced model covering the period of time over which the system should be monitored. Figure 4.21 indicates a time-sliced model constructed based on the static network shown in Figure 4.20. Each time-slice consists of the structure shown in Figure 4.20 while the development of the system is specified by links between variables of different time-slices.



**Fig. 4.21.** The structure of a dynamic model with  $n$  time-slices.

The *temporal links* of a time-slice  $t_i$  is the set of links from variables of time-slice  $t_{i-1}$  into variables of time-slice  $t_i$ . The temporal links of time slice  $t_i$  define the conditional distribution of the variables of time slice  $t_i$  given the variables of time slice  $t_{i-1}$ . The temporal links connect variables of adjacent time slices. For instance, the temporal links of time-slice  $t_2$  in Figure 4.21 is the set  $\{(X_1^1, X_1^2), (X_3^1, X_3^2)\}$ .

The *interface* of a time-slice is the set of variables with parents in the previous time-slice. For instance, the interface of time-slice  $t_2$  in Figure 4.21 is the set  $\{X_1^2, X_3^2\}$ .

Three additional concepts are often used in relation to dynamic models. Let  $i$  be the current time step, then *smoothing* is the process of querying about the state of the system at a previous time step  $j < i$  given evidence about the system at time  $i$ , *filtering* is the process of querying about the state of the system at the current time step, and *prediction* is the process of querying about the state of the system at a future time step  $j > i$ .

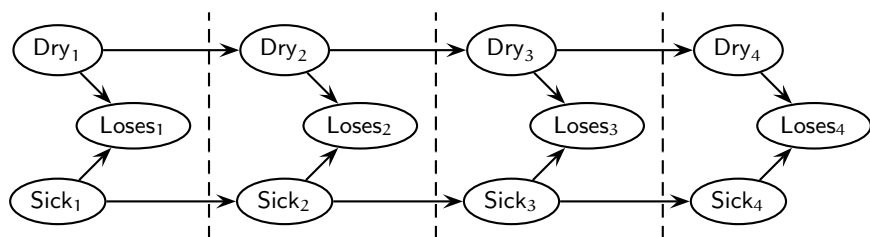
A dynamic Bayesian network is *stationary* when the transition probability distributions are invariant between time steps. A dynamic Bayesian network is first-order Markovian when the variables at time step  $i + 1$  are d-separated

from the variables at time step  $i - 1$  given the variables at time step  $i$ . When a system is stationary and Markovian, the state of the system at time  $i + 1$  only depends on its state at time  $i$ , and the probabilistic dependence relations are the same for all  $i$ . The Markovian property implies that arcs between time slices only go from one time slice to the subsequent time slice.

A dynamic Bayesian network is referred to as either a *dynamic Bayesian network* (DBN) or a *time-sliced Bayesian network* (TBN). See Kjærulff (1995) for more details on dynamic Bayesian networks.

*Example 4.17 (Apple Jack's Finest Tree).* Figure 4.1 of Example 4.1 on page 66 shows the Apple Jack network. The network is used for reasoning about the cause of Apple Jack's finest apple tree losing its leaves. The network is static and models the dependence relations between two diseases and a symptom at four specific points in time where Apple Jack is observing his tree.

Consider the case where Apple Jack is monitoring the development of the disease over a period of time by observing the tree each day in the morning. In this case the level of dryness of the tree on a specific day will depend on the level of dryness on the previous day and impact the level of dryness on the next day; similarly for the level of sickness. The levels of dryness and sickness on the next day are independent of the levels of dryness and sickness on the previous day given the levels of dryness and sickness on the current day. This can be captured by a dynamic model.



**Fig. 4.22.** A model with four time-slices.

Figure 4.22 shows a dynamic model with four time slices. Each time step models the state of the apple tree at a specific point in time (the dashed lines illustrates the separation of the model into time slices). The conditional probability distributions  $P(\text{Dry}_i | \text{Dry}_{i-1})$  and  $P(\text{Sick}_i | \text{Sick}_{i-1})$  are the transition probability distributions. The interface between time slices  $i - 1$  and  $i$  consists of  $\text{Dry}_i$  and  $\text{Sick}_i$ .

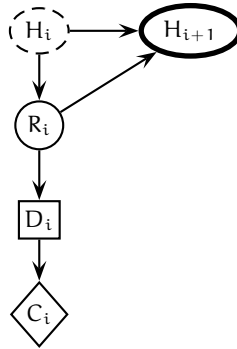
Assume that it is the second day when Apple Jack is observing his tree. The observations on **Loses** of the first and second day are entered as evidence on the corresponding variables. Filtering is the task of computing the probability of the tree being sick on the second day, smoothing is the task of computing the

probability of sickness on the first day and prediction is the task of computing the probability of the tree being sick on the third or fourth day.

Dynamic models are not restricted to be Bayesian networks. Influence diagrams and LIMIDs can also be represented as dynamic models.

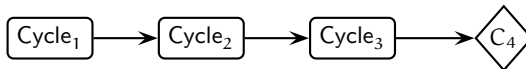
Time-sliced networks are often represented using object-oriented networks as the following example illustrates.

*Example 4.18 (Breeding Pigs).* Example 4.13 shows a LIMID representation of a decision problem related to breeding pigs, see Figure 4.15 on page 91. The decision problem is in fact modeled as a time-sliced model where the structure of each time-slice representing a test-and-treat cycle is shown in Figure 4.23.



**Fig. 4.23.** The test-and-treat cycle of the Breeding Pigs network in Figure 4.15.

Three instances of the network class in Figure 4.23 are constructed to create the network in Figure 4.24. The use of object-oriented modeling has simplified the network construction.



**Fig. 4.24.** The Breeding Pigs network as a time-sliced OOPN.

The network in Figure 4.24 is equivalent to the network in Figure 4.15 on page 91.

Kjærulff (1995) has described a computational system for dynamic time-sliced Bayesian networks. The system implemented is referred to as dHugin. Boyen & Koller (1998) have described an approximate inference algorithm for solving dynamic Bayesian networks with bounds on the approximation error.

## 4.5 Summary

In this chapter we have introduced probabilistic networks for reasoning and decision making under uncertainty. A probabilistic network represents and processes probabilistic knowledge. The qualitative component of a probabilistic network encodes a set of (conditional) dependence and independence statements among a set of random variables, informational precedence, and preference relations. The quantitative component specifies the strengths of dependence relations using probability theory and preference relations using utility theory.

We have introduced discrete Bayesian network models and CLG Bayesian network models for reasoning under uncertainty. A discrete Bayesian network supports the use of discrete random variables whereas a CLG Bayesian network supports the use of a mixture of continuous and discrete random variables. The continuous variables are constrained to be conditional linear Gaussian variables. The chapter contains a number of examples that illustrate the use of Bayesian networks for reasoning under uncertainty.

Discrete influence diagrams, CLQG influence diagrams, and limited memory influence diagrams were introduced as models for reasoning and decision making under uncertainty. An influence diagram is a Bayesian network augmented with decision variables, informational precedence relations, and preference relations. A discrete influence diagram supports the use of discrete random and decision variables with an additively decomposing utility function. A CLQG influence diagram supports the use of a mixture of continuous and discrete variables. The continuous random variables are constrained to be conditional linear Gaussian variables while the utility function is constrained to be linear-quadratic. A limited memory influence diagram is an extension of the discrete influence diagram where the assumptions of no-forgetting and a total order on the decisions are relaxed. This allows us to model a large set of decision problems that cannot be modeled using the traditional influence diagram representation. The chapter contains a number of examples that illustrate the use of influence diagrams for decision making under uncertainty.

Finally, we have introduced OOPNs. The basic OOPN mechanisms introduced support a type of object-oriented specification of probabilistic networks, which makes it simple to reuse models, to encapsulate sub-models, and to perform model construction at different levels of abstraction. The chapter contains a number of examples that illustrates the use of the basic OOPN mechanisms in the model development process. OOPNs are well-suited for constructing time-sliced networks. Time-sliced networks are used to represent dynamic models.

In Chapter 5 we discuss techniques for solving probabilistic networks.

## Exercises

**Exercise 4.1.** Peter and Eric are chefs at Restaurant Bayes. Peter works six days a week while Eric works one day a week. In 90% of the cases Peter's food is high quality while Eric's food is high quality in 50% of the cases. One evening Restaurant Bayes serves an awful meal.

Is it fair to conclude that Eric prepared the food that evening?

**Exercise 4.2.** One in a thousand people has a prevalence for a particular heart disease. There is a test to detect this disease. The test is 100% accurate for people who have the disease and is 95% accurate for those who do not (this means that 5% of people who do not have the disease will be wrongly diagnosed as having it).

If a randomly selected person tests positive what is the probability that the person actually has the heart disease?

**Exercise 4.3.** Assume a math class is offered once every semester while an AI class is offered twice. The number of students taking a class depends on the subject. On average 120 students take AI ( $\sigma^2 = 500$ ) while 180 students take math ( $\sigma^2 = 1000$ ). Assume that on average 25% pass the AI exam ( $\sigma^2 = 400$ ) while 50% pass the math exam ( $\sigma^2 = 500$ ).

- What is the average number of students passing either a math or AI an exam?
- What is the average number of students passing a math exam?
- What is the average number of students taking a math class when 80 students pass the exam?

**Exercise 4.4.** Frank goes to the doctor because he believes that he has got the flu. At this particular time of the year, the doctor estimates that one out of 1000 people suffers from the flu. The first thing the doctor checks is whether Frank appears to have the standard symptoms of the flu; if Frank suffers from the flu, then he will exhibit these symptoms with probability 0.9, but if he does not have the flu he may still have these symptoms with probability 0.05. After checking whether or not Frank has the symptoms, the doctor can decide to have a test performed which may reveal more information about whether or not Frank suffers from the flu; the cost of performing the test is €40. The test can either give a positive or a negative result, and the frequency of false positives and false negatives is 0.05 and 0.1, respectively. After observing the test result (if any) the doctor can decide to administer a drug that with probability 0.6 may shorten the sickness period if Frank suffers from the flu (if he has not got the flu, then the drug has no effect). The cost of administering the drug is €100, and if the sickness period is shortened the doctor estimates that this is worth €1000.

- Construct an influence diagram for the doctor from the description above.

(b) Specify the probability distributions and the utility functions for the influence diagram.

**Exercise 4.5.** Assume that Frank is thinking about buying a used car for €20,000, and the market price for similar cars with no defects is €23,000. The car may, however, have defects which can be repaired at the cost of €5000; the probability that the car has defects is 0.3. Frank has the option of asking a mechanic to perform (exactly) one out of two different tests on the car. **Test<sub>1</sub>** has three possible outcomes, namely no-defects, defects and inconclusive. For **Test<sub>2</sub>** there are only two possible outcomes (no-defects and defects). If Frank chooses to have a test performed on the car, the mechanic will report the result back to Frank who then decides whether or not to buy the car; the cost of **Test<sub>1</sub>** is €300 and the cost of **Test<sub>2</sub>** is €1000.

- (a) Construct an influence diagram for Frank’s decision problem.
- (b) Calculate the maximum expected utility and the optimal strategy for the influence diagram; calculate the required probabilities from the joint probability table (over the variables **Test<sub>1</sub>**, **Test<sub>2</sub>** and **StateOfCar**) specified below.

		<b>Test<sub>1</sub></b>		
		no-defects	defects	inconclusive
<b>Test<sub>2</sub></b>	no-defects	(0.448, 0.00375)	(0.028, 0.05625)	(0.084, 0.015)
	defects	(0.112, 0.01125)	(0.007, 0.16875)	(0.021, 0.045)

**Exercise 4.6.** An environmental agency visits a site where a chemical production facility has previously been situated. Based on the agency’s knowledge about the facility, they estimate that there is a 0.6 risk that chemicals from the facility have contaminated the soil. If the soil is contaminated (and nothing is done about it) all people in the surrounding area will have to undergo a medical examination due to the possible exposure; there are 1000 people in the area, and the cost of examining/treating one person is \$100. To avoid exposure, the agency can decide to remove the top layer of the soil which, in case the ground is contaminated, will completely remove the risk of exposure; the cost of removing the soil is \$30,000. Before making the decision of whether or not to remove the top layer of soil, the agency can perform a test which will give a positive result (with probability 0.9) if the ground is contaminated; if the ground is not contaminated the test will give a positive result with probability 0.01. The cost of performing the test is \$1000.

- (a) Construct an influence diagram for the environmental agency from the description above.
- (b) Specify the probability distributions and the utility functions for the influence diagram.

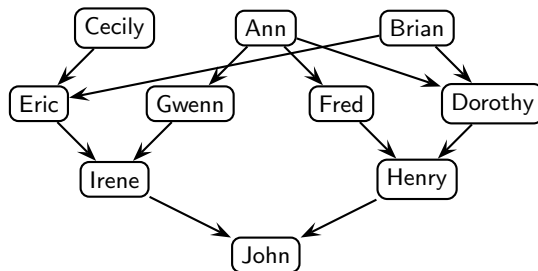
**Exercise 4.7.** A company has observed that one of their software systems is unstable, and they have identified a component which they suspect is the cause

of the instability. The company estimates that the prior probability for the component being faulty is 0.01, and if the component is faulty then it causes the system to become unstable with probability 0.99; if the component is not faulty, then the system may still be unstable (due to some other unspecified element) with probability 0.001.

To try to solve the problem the company must first decide whether to *patch* the component at a cost €10,000 : if the component is faulty, then the patch will solve the fault with probability 0.95 (there may be several things wrong, not all of which may be covered by the patch), but if the component is not faulty then the patch will have no effect. The company also knows that in the near future the vendor of the component will make another patch available at the cost of €20,000; the two patches focus on different parts of the component. This new patch will solve the problem with probability 0.99, and (as for the first patch) if the component is not faulty then the patch will have no effect. Thus, after deciding on the first patch, the company observes whether or not the patch solved the problem (i.e., is the system still unstable?) and it then has to decide on the second patch. The company estimates that (after the final decision has been made) the value of having a fully functioning component is worth €100,000.

- Construct an influence diagram for the company from the description above.
- Specify the probability distributions and the utility functions for the influence diagram.

**Exercise 4.8.** Consider a stud farm with ten horses where Cecily has unknown mare and sire, John has mare Irene and sire Henry, Henry has mare Dorothy and sire Fred, Irene has mare Gwenn and sire Eric, Gwenn has mare Ann and unknown sire, Eric has mare Cecily and sire Brian, Fred has mare Ann and unknown sire, Brian has unknown mare and sire, Dorothy has mare Ann and sire Brian, and Ann has unknown mare and sire, see Figure 4.25.



**Fig. 4.25.** The stud farm pedigree.

A sick horse has genotype  $aa$ , a carrier of the disease has genotype  $aA$ , and a non-carrier has genotype  $AA$ .  $P(aa, aA, AA) = (0.1, 0.2, 0.7)$

- (a) Construct an object-oriented network representation of the stud farm problem.
- (b) What is the probability of each horse being sick/a carrier/a non-carrier once we learn that John is sick?



## Solving Probabilistic Networks

We build knowledge bases in order to formulate our knowledge about a certain problem domain in a structured way. The purpose of the knowledge base is to support our reasoning about events and decisions in a domain with inherent uncertainty. The fundamental idea of solving a probabilistic network is to exploit the structure of the knowledge base to reason efficiently about the events and decisions of the domain taking the inherent uncertainty into account.

An expert system consists of a knowledge base and an inference engine. The inference engine is used to solve queries against the knowledge base. In the case of probabilistic networks, we have a clear distinction between the knowledge base and the inference engine. The knowledge base is the Bayesian network or influence diagram, whereas the inference engine consists of a set of generic methods that applies the knowledge formulated in the knowledge base on task-specific data sets, known as evidence, to compute solutions to queries against the knowledge base. The knowledge base alone is of limited use if it cannot be applied to update our belief about the state of the world or to identify (optimal) decisions in the light of new knowledge.

As we saw in the previous chapter, the knowledge bases we consider are probabilistic networks. A probabilistic network may be an efficient representation of a joint probability distribution or a joint expected utility function. In the former case the model is a Bayesian network, while in the latter case it is an influence diagram.

In this chapter we consider the process of solving probabilistic networks. As the exact nature of solving a query against a probabilistic network depends on the type of model, the solution process of Bayesian networks and influence diagrams are considered separately in the following sections.

Section 5.1 considers probabilistic inference in Bayesian networks as the task of computing posterior beliefs in the light of evidence. A number of different approaches to inference are considered. We consider variable elimination, query-based inference, arc reversal, and message passing in junction trees. The inference process in discrete Bayesian networks is treated in detail, while the

inference process in CLG Bayesian networks and CLQG influence diagrams is outlined. In Section 5.2 we consider the task of solving decision models. Solving a decision model amounts to computing maximum expected utilities. We derive a generic method for solving influence diagrams and LIMIDs.

Parts of this chapter have appeared in Madsen, Jensen, Kjærulff & Lang (2005).

## 5.1 Probabilistic Inference

We build Bayesian network models in order to support efficient reasoning under uncertainty in a given domain. Reasoning under uncertainty is the task of computing our updated beliefs in (unobserved) events given observations on other events, i.e., evidence.

### 5.1.1 Inference in Discrete Bayesian Networks

One particular type of probabilistic inference task in Bayesian networks is the task of computing the posterior marginal of an unobserved variable  $Y$  given a (possibly empty) set of evidence  $\varepsilon$ , i.e.,  $P(Y|\varepsilon)$ . Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  be a Bayesian network over the set of discrete random variables  $\mathcal{X} = \{X_1, \dots, X_n\}$ , and assume that  $\varepsilon = \emptyset$ . Exploiting the chain rule for Bayesian networks (see e.g., Equation 4.1 on page 65), for variable  $Y \in \mathcal{X}$ , we may compute

$$\begin{aligned} P(Y) &= \sum_{X \in \mathcal{X} \setminus \{Y\}} P(X) \\ &= \sum_{X \in \mathcal{X} \setminus \{Y\}} \prod_{X_v \in \mathcal{X}} P(X_v | X_{\text{pa}(v)}). \end{aligned} \quad (5.1)$$

This is the prior marginal distribution  $P(Y)$  of  $Y$ . The prior marginal of all variables may be computed by repetition for each variable.

*Example 5.1.* Given the example of Apple Jack (Example 4.1 on page 66), we may consider the task of computing the prior marginal distribution  $P(L)$  over the events that the tree does lose its leaves and that the tree does not lose its leaves. The distribution  $P(L)$  may be computed as

$$P(L) = \sum_S \sum_D P(S)P(L|S, D)P(D).$$

Using the quantification of the model specified as part of Example 4.1, we arrive at the prior distribution  $P(L) = (0.82, 0.18)$ . Hence, *a priori*, there is an 18% probability that the tree will lose its leaves.

The above approach does not incorporate evidence into the inference task. In addition, it is a very inefficient approach for non-trivial Bayesian networks because the joint distribution  $P(\mathcal{X})$  over  $\mathcal{X}$  is constructed as an intermediate step and because a lot of calculations are repeated.

As we will see, it is possible to develop a more efficient approach to probabilistic inference by exploiting the independence relations induced by the structure of the DAG and the evidence, and by minimizing the repetition of calculations. Having said that, let us turn to the general case of computing the posterior marginal  $P(X|\varepsilon)$  of a variable,  $X$ , given evidence  $\varepsilon$ .

Let  $\varepsilon = \{\varepsilon_1, \dots, \varepsilon_m\}$  be a non-empty set of evidence over variables  $\mathcal{X}(\varepsilon)$ . For a (non-observed) variable  $X_j \in \mathcal{X}$  of  $\mathcal{N}$ , the task is to compute the posterior probability distribution  $P(X_j|\varepsilon)$ . This can be done by exploiting the chain rule factorization of the joint probability distribution induced by  $\mathcal{N}$ :

$$\begin{aligned}
 P(X_j|\varepsilon) &= \frac{P(\varepsilon|X_j)P(X_j)}{P(\varepsilon)} = \frac{P(X_j, \varepsilon)}{P(\varepsilon)} \\
 &\propto P(X_j, \varepsilon) \\
 &= \sum_{Y \in \mathcal{U} \setminus \{X_j\}} P(\mathcal{X}, \varepsilon) \\
 &= \sum_{Y \in \mathcal{U} \setminus \{X_j\}} \prod_{X_i \in \mathcal{X}} P(X_i|X_{\text{pa}(\mathbf{v}_i)}) \mathcal{E}_\varepsilon \\
 &= \sum_{Y \in \mathcal{U} \setminus \{X_j\}} \prod_{X_i \in \mathcal{X}} P(X_i|X_{\text{pa}(\mathbf{v}_i)}) \prod_{X \in \mathcal{X}(\varepsilon)} \mathcal{E}_X
 \end{aligned}$$

for each  $X_j \notin \mathcal{X}(\varepsilon)$ , where  $\mathcal{E}_X$  is the evidence function for  $X \in \mathcal{X}(\varepsilon)$  and  $\mathbf{v}_i$  is the node representing  $X_i$ . Notice that

$$L(X_j|\varepsilon) = P(\varepsilon|X_j) = \sum_{Y \in \mathcal{X} \setminus \{X_j\}} \prod_{i \neq j} P(X_{\mathbf{v}_i}|X_{\text{pa}(\mathbf{v}_i)}) \prod_{X \in \mathcal{X}(\varepsilon)} \mathcal{E}_X \quad (5.2)$$

is the likelihood function of  $X_j$  given  $\varepsilon$ . Since  $P(X_j)$  may be obtained by inference over the empty set of evidence, we can — using Bayes' rule — compute

$$P(X_j|\varepsilon) \propto L(X_j|\varepsilon)P(X_j).$$

The proportionality factor is the normalization constant  $\alpha = P(\varepsilon)$ , which is easily computed from  $P(\mathcal{X}, \varepsilon)$  by summation over  $\mathcal{X}$  as  $\alpha = \sum_{\mathcal{X}} P(\mathcal{X}, \varepsilon)$ .

*Example 5.2.* One evening when Apple Jack is taking his usual after-dinner walk in the garden, he observes his finest apple tree to be losing its leaves. Given that he knows that this may be an indication of the tree being sick, he starts wondering whether or not the tree is sick.

Apple Jack is interested in the probability of the tree being sick given the observation on the tree losing its leaves

$$\begin{aligned}
P(S|\varepsilon) &= \frac{P(S, \varepsilon)}{P(\varepsilon)} \\
&= \frac{\sum_S \sum_D P(S)P(L|S, D)P(D)\varepsilon_L}{P(\varepsilon)} \\
&\propto (0.0927, 0.0905),
\end{aligned}$$

where  $\varepsilon_L = (0, 1)$  is the evidence function reflecting the tree losing its leaves. The normalization constant is  $\alpha = P(\varepsilon) = P(S = \text{no}|\varepsilon) + P(S = \text{yes}|\varepsilon) = 0.0927 + 0.0905 = 0.1832$ . This produces the posterior distribution  $P(S|\varepsilon) = (0.506, 0.494)$  over the tree losing its leaves. Hence, there is an increased probability that the tree is sick when it has been observed to lose its leaves. The prior distribution on the tree being sick is  $P(S) = (0.9, 0.1)$ .

In general, probabilistic inference is an NP-hard task (Cooper 1990). Even approximate probabilistic inference is NP-hard (Dagum & Luby 1993). For certain classes of Bayesian network models the complexity of probabilistic inference is polynomial or even linear in the number of variables in the network. The complexity is polynomial when the graph of the Bayesian network is a poly-tree (Kim & Pearl 1983, Pearl 1988) (a directed graph  $\mathcal{G}$  is called a *poly-tree*, if its underlying undirected graph is singly connected), while it is linear when the graph of the Bayesian network is a tree.

The most critical problem related to the efficiency of the inference process is that of finding the optimal order in which to perform the computations. The inference task is, in principle, solved by performing a sequence of multiplications and additions.

## Query-Based Inference

One approach to inference is to consider the inference task as the task of computing the posterior distribution of a set of variables. This is referred to as query based inference. We define the notion of a query,  $Q$ , against a Bayesian network model  $\mathcal{N}$  as follows.

**Definition 5.1 (Query).** *Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  be a Bayesian network model. A query  $Q$  is a three-tuple  $Q = (\mathcal{N}, \mathcal{T}, \varepsilon)$  where  $\mathcal{T} \subseteq \mathcal{X}$  is the target set and  $\varepsilon$  is the evidence set.*

The solution of a query,  $Q$ , is the posterior distribution over the target, i.e.,  $P(\mathcal{T}|\varepsilon)$ . A variable  $X$  is a target variable if  $X \in \mathcal{T}$ . Notice that computing all posterior marginals of a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  corresponds to solving  $|\mathcal{X}|$  queries, i.e.,  $Q = (\mathcal{N}, \{X\}, \varepsilon)$  for each  $X \in \mathcal{X}$ .

Prior to solving the query  $Q$ , the graph  $\mathcal{G}$  of  $\mathcal{N}$  may be pruned to include only variables relevant for the query. One class of variables which may be pruned from the graph without any computation is the class of barren variables, see Section 3.3.4 on page 49 for an example. Here we give a formal definition of a barren variable.

**Definition 5.2 (Barren Variable).** Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  be a Bayesian network and let  $Q = (\mathcal{N}, \mathcal{T} \subseteq \mathcal{X}, \varepsilon)$  be a query against  $\mathcal{N}$ . A variable  $X$  is a barren variable with respect to  $Q$ , if  $X \notin \mathcal{T}$ ,  $X \notin \varepsilon$ , and all descendants,  $\text{de}(X)$ , of  $X$  are barren.

When a variable  $X$  is classified as a barren variable, it is always relative to a target and given a set of evidence. A barren variable does not add any information to the inference process. It is computationally irrelevant to  $Q$ .

Once all barren variables with respect to  $Q$  have been pruned from the graph  $\mathcal{G}$ , the inference task can be solved by variable elimination as described in the previous section.

In addition to the concept of a barren variable, there is the concept of a *nuisance variable*.

**Definition 5.3 (Nuisance Variable).** Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  be a Bayesian network and let  $Q = (\mathcal{N}, \mathcal{T} \subseteq \mathcal{X}, \varepsilon)$  be a query against  $\mathcal{N}$ . A non-barren variable  $X$  is a nuisance variable with respect to  $Q$ , if  $X \notin \mathcal{T}$ ,  $X \notin \varepsilon$ , and  $X$  is not on a path between any pair of variables  $Y \in \mathcal{T}$  and  $Z \in \varepsilon$ .

Notice that a nuisance variable is computationally relevant for a query  $Q$ , but it is not on a path between any pair of evidence and query variables. Given a query and a set of evidence variables, the contribution from a nuisance variable does not depend on the observed values of the evidence variables. Hence, if a query is to be solved with respect to multiple instantiations over the evidence variables, then the nuisance variables (and barren variables) may be eliminated in a preprocessing step to obtain the *relevant network* (Lin & Druzdzel 1997). The relevant network consists of target variables, evidence variables, and variables on paths between target and evidence variables only.

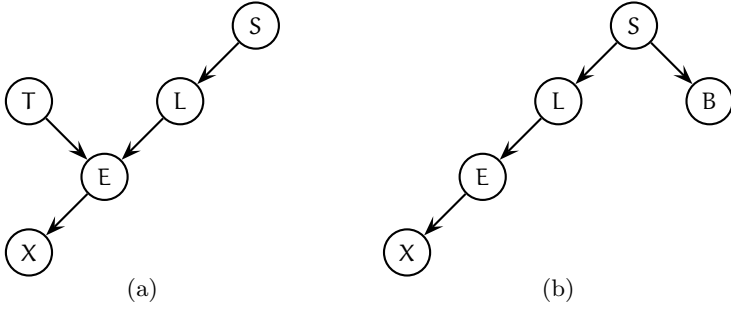
*Example 5.3.* Returning to the Chest Clinic example (Example 4.2 on page 68), we may consider the task of computing the probability of each disease given the observations that the patient is a smoker and has a positive X-ray result. That is, we need to compute  $P(Y|\varepsilon)$  for  $Y \in \{T, L, B\}$  and  $\varepsilon = \{S = \text{yes}, X = \text{yes}\}$ .

The variables  $\{A, T\}$  are nuisance variables with respect to posteriors for  $B$  and  $L$ . The variable  $D$  is a barren variable with respect to the posteriors for  $B$ ,  $T$ , and  $L$ , whereas  $B$  is a barren variable with respect to the posteriors for  $T$  and  $L$ . Figure 5.1 shows the relevant networks for (a) computing  $P(T|\varepsilon)$  and  $P(L|\varepsilon)$ , and for (b) computing  $P(B|\varepsilon)$ .

The approach to inference outlined above may be referred to as a *direct approach*. Arc reversal is a specific type of direct approach to inference (Olmsted 1983, Shachter 1986).

## Arc Reversal

In Section 3.4.1 on page 52 we illustrated how application of Bayes' rule can be given a graphical interpretation as arc reversal. We mentioned that Olmsted



**Fig. 5.1.** The relevant networks for computing (a)  $P(T|\varepsilon)$  and  $P(L|\varepsilon)$ , and (b)  $P(B|\varepsilon)$ .

(1983) and Shachter (1986) have exploited this view of inference in their arc reversal algorithms for inference in probabilistic networks. Here we consider the process in more detail.

Let  $\mathcal{G}$  be the DAG of a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  and assume a query  $Q = (\mathcal{N}, \{Z\}, \emptyset)$  against  $\mathcal{N}$ . The inference task is to compute  $P(Z)$  by eliminating all variables  $\mathcal{X} \setminus \{Z\}$ .

The inference process on  $\mathcal{G}$  has a natural graphical interpretation as a sequence of arc reversals and barren variable eliminations. The fundamental idea is to adjust the structure of  $\mathcal{G}$  such that all variables except  $Z$  are pruned as barren variables while maintaining the underlying properties of the joint probability distributions over the remaining variables. The structure of  $\mathcal{G}$  is adjusted through a sequence of arc reversal operations.

Assume  $X_w$  is the next variable to be eliminated as a barren variable. Let  $X_w$  have parents  $X_{\text{pa}(w)} = X_i \cup X_j$  and  $X_v$  have parents  $X_{\text{pa}(v)} = \{X_w\} \cup X_j \cup X_k$  where  $X_i \cap X_j = X_i \cap X_k = X_j \cap X_k = \emptyset$  such that  $X_i = X_{\text{pa}(w)} \setminus X_{\text{pa}(v)}$  are the parents specific for  $X_w$ ,  $X_j = X_{\text{pa}(w)} \cap X_{\text{pa}(v)}$  are the common parents, and  $X_k = X_{\text{pa}(v)} \setminus X_{\text{fa}(w)}$  are the parents specific for  $X_v$ .

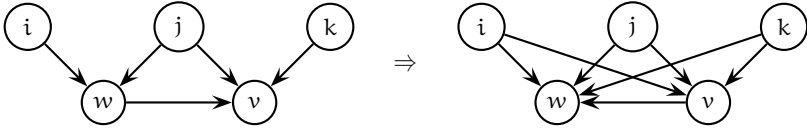
The reversal of arc  $(w, v)$  proceeds by setting  $X_{\text{pa}(w)} = X_i \cup X_j \cup X_k \cup \{X_v\}$  and  $X_{\text{pa}(v)} = X_i \cup X_j \cup X_k$  as well as performing the computations specified below, see Figure 5.2 for a graphical representation

$$P(X_v | X_i, X_j, X_k) = \sum_{X_w} P(X_w | X_i, X_j) P(X_v | X_w, X_j, X_k) \quad (5.3)$$

$$P(X_w | X_v, X_i, X_j, X_k) = \frac{P(X_w | X_i, X_j) P(X_v | X_w, X_j, X_k)}{P(X_v | X_i, X_j, X_k)}. \quad (5.4)$$

The operation of reversing an arc changes the structure of  $\mathcal{G}$  without changing the underlying joint probability distribution over  $\mathcal{X}$  induced by  $\mathcal{N}$ .

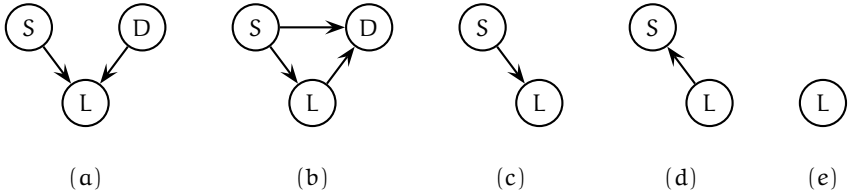
Once the arc  $(w, v)$  has been reversed, the variable  $X_w$  is a barren variable relative to the other variables (given the empty set of evidence), and can be pruned from  $\mathcal{G}$  without further computations.



**Fig. 5.2.** An illustration of reversal of the arc  $(w, v)$ .

The basic idea of the inference process known as arc reversal is to perform a sequence of arc reversals and barren variable eliminations on the DAG  $\mathcal{G}$  until a desired marginal or conditional is obtained. In this process a valid Bayesian network structure is maintained throughout the inference process.

*Example 5.4.* We may compute the prior probability distribution  $P(L)$  in the Apple Jack example (see Example 4.1 on page 66) using a sequence of arc reversals and barren variable eliminations as indicated in Figure 5.3.



**Fig. 5.3.** Computing  $P(L)$  by arc reversal.

Notice that the arc reversal method does not have worse complexity than variable elimination.

Arc reversal is not a local computation algorithm in the sense that when reversing an arc  $(w, v)$ , it is necessary to test for existence of a directed path from  $w$  to  $v$  not containing  $(w, v)$ . If such a path exists, then the arc  $(w, v)$  cannot be reversed until one or more other arcs have been reversed as reversing  $(w, v)$  would otherwise create a directed path.

## Graphical Representation of Inference

We may define the task of solving a Bayesian network model  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  as the problem of computing the posterior marginal  $P(X|\varepsilon)$  given a set of evidence  $\varepsilon$  for all variables  $X \in \mathcal{X}$ .

When defining the task of probabilistic inference as the task of computing the posterior marginals  $P(X|\varepsilon)$  for all  $X$  given evidence  $\varepsilon$ , the most common approach is to use a secondary computational structure. Performing inference

in a secondary computational structure aims at reusing calculations solving all queries simultaneously.

From Equation 5.1 on page 108 we should notice the direct correspondence between the acyclic, directed graph  $\mathcal{G}$  and the factorization of the joint probability distribution  $P(\mathcal{X})$  over  $\mathcal{X}$ . The domain of each factor in the factorization corresponds to a node and its parents. The head of the factor is the child node whereas the tail consists of the parents. Furthermore, if we drop the distinction between head and tail we see that the domain of each factor corresponds to a *clique* (a clique is a maximal complete subgraph) of  $\mathcal{G}^m$  — the moralization of  $\mathcal{G}$ . This is exploited to build a secondary structure for performing inference.

Assume we are in the process of computing  $P(X_i)$ . Let  $Y$  be the first random variable to eliminate. The elimination process proceeds by local computation in order to maintain efficiency (i.e., we exploit the distributive law to maintain the factorization of the joint probability distribution — see Section 3.3.3 on page 47). The set of probability potentials  $\mathcal{P}$  can be divided into two disjoint subsets with respect to  $Y$ . Let  $\mathcal{P}_Y \subseteq \mathcal{P}$  be the subset of probability potentials including  $Y$  in the domain

$$\mathcal{P}_Y = \{P \in \mathcal{P} \mid Y \in \text{dom}(P)\},$$

where  $\text{dom}(P)$  denotes the domain of  $P$  (i.e., the set of variables over which it is defined). Then  $\mathcal{P} \setminus \mathcal{P}_Y$  is the set of probability potentials not including  $Y$  in their domain. Let  $\phi_Y$  be the probability potential obtained by eliminating  $Y$  (by summation) from the combination of all probability potentials in  $\mathcal{P}_Y$ . Using  $\phi_Y$  as well as a generalized version of the distributive law, we may rewrite Equation 5.1 on page 108 as

$$\begin{aligned} P(X_i) &= \sum_{X \in \mathcal{X} \setminus \{X_i\}} \prod_{X_v \in \mathcal{X}} P(X_v \mid X_{\text{pa}(v)}) \\ &= \sum_{X \in \mathcal{X} \setminus \{X_i\}} \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi \prod_{\phi' \in \mathcal{P}_Y} \phi' \\ &= \sum_{X \in \mathcal{X} \setminus \{X_i, Y\}} \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi \sum_Y \prod_{\phi' \in \mathcal{P}_Y} \phi' \\ &= \sum_{X \in \mathcal{X} \setminus \{X_i, Y\}} \phi_Y \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi. \end{aligned} \tag{5.5}$$

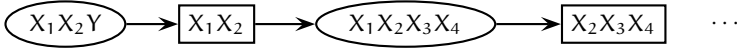
Equation 5.5 specifies a decomposition of the joint probability distribution over  $\mathcal{X} \setminus \{Y\}$ . The decomposition has the form of Equation 5.1. The decomposition is the product over the elements of  $\mathcal{P} \setminus \mathcal{P}_Y \cup \{\phi_Y\}$ . In addition, we have performed the elimination over  $Y$  by local computations only involving potentials of which  $Y$  is a domain variable. We say that the set

$$\mathcal{P} \setminus \mathcal{P}_Y \cup \{\phi_Y\}$$



is a reduction of  $\mathcal{P}$  where  $Y$  has been eliminated. The elimination of the next variable to be eliminated may proceed in the same manner on  $\mathcal{P} \setminus \mathcal{P}_Y \cup \{\phi_Y\}$ . The order in which variables are eliminated is the *elimination order*.

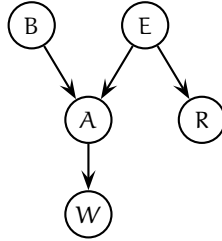
An example of this process may be depicted graphically as shown in Figure 5.4 where we assume  $\text{dom}(\phi_Y) = \{X_1, X_2\}$ . The arrows in the figure are used to illustrate the flow of computations.



**Fig. 5.4.** A graphical illustration of the process of eliminating  $Y$  from  $\phi(X_1, X_2, Y)$  and  $X_1$  from  $\phi(X_1, X_2, X_3, X_4)$ , where the ovals represent the domain of a potential before elimination, and rectangles represent the domain of a potential after elimination.

The elimination of  $Y$  from  $\phi(X_1, X_2, Y)$  creates a potential over  $\phi(X_1, X_2)$  which is included in the elimination of the next variable  $X_1$  to be eliminated. In this way the process continues until the desired marginals are obtained. Let us consider an even more concrete example.

*Example 5.5 (Burglary or Earthquake on page 25).* The Bayesian network shown in Figure 2.3 on page 26, is repeated in Figure 5.5.



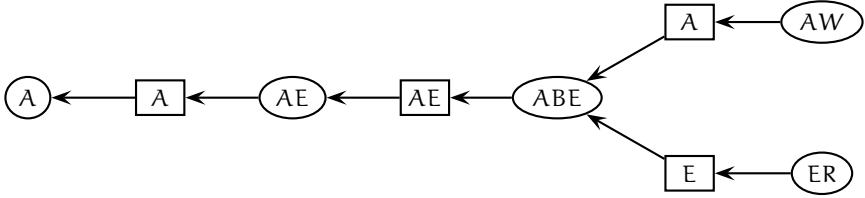
**Fig. 5.5.** The Burglary or Earthquake network.

The prior marginal on  $A$  may be computed by elimination of  $\{B, E, R, W\}$  as follows

$$P(A) = \sum_E P(E) \sum_B P(B) P(A|B, E) \sum_R P(R|E) \sum_W P(W|A). \quad (5.6)$$

Figure 5.6 shows a graphical representation of the computations and potentials created the during process of computing  $P(A)$ .

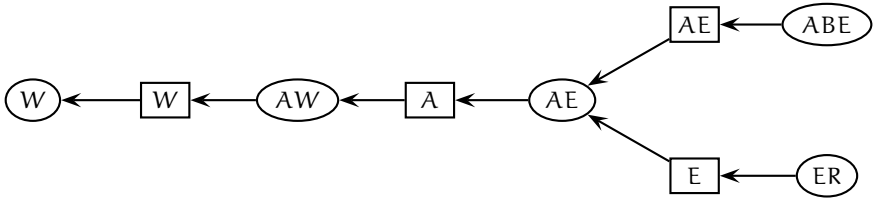
Similarly, the prior marginal distribution over  $W$  may be computed by elimination of  $\{A, B, E, R\}$  as follows



**Fig. 5.6.** A graphical illustration of the process of computing  $P(A)$  in Equation 5.6, where the ovals represent the domain of a potential before elimination, and rectangles represent the domain of a potential after elimination.

$$P(W) = \sum_A P(W|A) \sum_E P(E) \sum_B P(B)P(A|B, E) \sum_R P(R|E). \quad (5.7)$$

Figure 5.7 shows a graphical representation of the computations and potentials created during the process of computing of  $P(W)$ .



**Fig. 5.7.** A graphical illustration of the process of computing  $P(W)$  in Equation 5.7, where the ovals represent the domain of a potential before elimination, and rectangles represent the domain of a potential after elimination.

Notice the similarity between the potentials created in the process of computing  $P(A)$  and  $P(W)$ . There is a significant overlap between the potentials created and therefore the calculations performed. This is no coincidence.

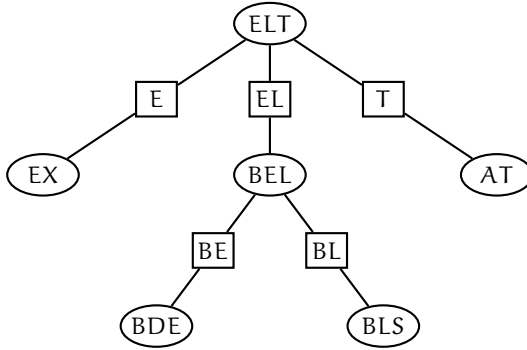
## Junction Trees

The task of probabilistic inference may be solved efficiently by local procedures operating on a secondary computational structure known as the *junction tree* (also known as a join tree and a Markov tree) representation of a Bayesian network (Jensen & Jensen 1994, Jensen et al. 1994).

The junction tree representation is efficient when solving the inference task for multiple sets of different evidence and target variables. A junction tree representation  $\mathcal{T}$  of a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  is a pair  $\mathcal{T} = (\mathcal{C}, \mathcal{S})$

where  $\mathcal{C}$  is the set of cliques and  $\mathcal{S}$  is the set of separators. The cliques  $\mathcal{C}$  are the nodes of  $\mathcal{T}$  whereas the separators  $\mathcal{S}$  annotate the links of the tree. Each clique  $C \in \mathcal{C}$  represents a maximal complete subset of pairwise connected variables of  $\mathcal{X}$ , i.e.,  $C \subseteq \mathcal{X}$ , of an undirected graph.<sup>1</sup> The link between two neighboring cliques  $C_i$  and  $C_j$  is annotated with the intersection  $S = C_i \cap C_j$ , where  $S \in \mathcal{S}$ .

*Example 5.6 (Chest Clinic).* Figure 4.2 on page 69 shows the DAG  $\mathcal{G}$  of the Chest Clinic network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$ , see Example 4.2 on page 68.



**Fig. 5.8.** A junction tree representation  $\mathcal{T}$  for the Chest Clinic network.

Figure 5.8 shows a junction tree representation  $\mathcal{T} = (\mathcal{C}, \mathcal{S})$  of the Chest Clinic network. The junction tree consists of cliques

$$\mathcal{C} = \{\{A, T\}, \{B, D, E\}, \{B, E, L\}, \{B, L, S\}, \{E, L, T\}, \{E, X\}\}$$

and separators

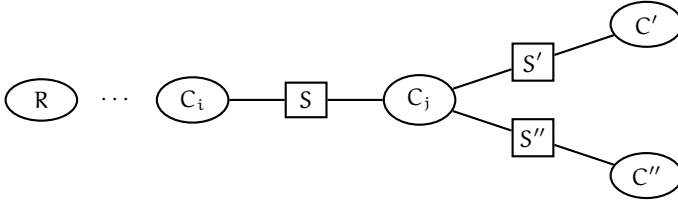
$$\mathcal{S} = \{\{B, E\}, \{B, L\}, \{E\}, \{E, L\}, \{T\}\}.$$

The structure of  $\mathcal{T}$  is determined from the structure of  $\mathcal{G}$ .

The process of creating a junction tree representation of a DAG is beyond the scope of this book. Instead we refer the interested reader to the literature, see, e.g., Cowell, Dawid, Lauritzen & Spiegelhalter (1999).

The junction tree serves as an excellent control structure for organizing the computations performed during probabilistic inference. Messages are passed between cliques of the junction tree in two sweeps such that a single message is passed between each pair of neighboring cliques in each sweep. This process is referred to as a *propagation of information*.

<sup>1</sup> The undirected graph is constructed from the moral graph  $\mathcal{G}^m$  of  $\mathcal{G}$  by adding undirected edges until the graph is triangulated. A graph is triangulated if every cycle of length greater than three has a chord.



**Fig. 5.9.** When  $C_j$  has absorbed information from its other neighbors,  $C_i$  can absorb from  $C_j$ .

Once the junction tree  $\mathcal{T} = (\mathcal{C}, \mathcal{S})$  has been constructed, a probability potential is associated with each clique  $C \in \mathcal{C}$  and each separator  $S \in \mathcal{S}$  between two adjacent cliques  $C_i$  and  $C_j$  where  $S = C_i \cap C_j$ , see Figure 5.9.

Inference involves the following steps:

- (1) Each item of evidence must be incorporated into the junction tree potentials. For each item of evidence, an evidence function is multiplied onto an appropriate clique potential.
- (2) Some clique  $R \in \mathcal{C}$  of  $\mathcal{T}$  is selected. This clique is referred to as the *root* of the propagation.
- (3) Then messages are passed toward the selected root. The messages are passed through the separators of the junction tree (i.e., along the links of the tree). These messages cause the potentials of the receiving cliques and separators to be updated. This phase is known as **COLLECTINFORMATION**.
- (4) Now messages are passed in the opposite direction (i.e., from the root toward the leaves of the junction tree). This phase is known as **DISTRIBUTEINFORMATION**.
- (5) At this point, the junction tree is said to be in equilibrium: The probability  $P(X|\epsilon)$  can be computed from any clique or separator containing  $X$  — the result will be independent of the chosen clique or separator.

Prior to the initial round of message passing, for each variable  $X_v \in \mathcal{X}$  we assign the conditional probability distribution  $P(X_v | X_{pa(v)})$  to a clique  $C$  such that  $X_{fa(v)} \subseteq C$ . Once all conditional probability distributions have been assigned to cliques, the distributions assigned to each clique are combined to form the initial clique potential.

*Example 5.7.* Consider again the junction tree of the Chest Clinic network shown in Figure 5.8. Each conditional probability distribution  $P \in \mathcal{P}$  is associated with a clique of  $\mathcal{T}$  such that  $\text{dom}(P) \subseteq C$  for  $C \in \mathcal{C}$ . Notice that the association of distributions with cliques is unique in this example.

The basic inference algorithm is as follows. Each separator holds a single potential over the separator variables, which initially is a unity potential. During propagation of information the separator and clique potentials are

updated. Consider two adjacent cliques  $C_i$  and  $C_j$  as shown in Figure 5.9. When a message is passed from  $C_j$  to  $C_i$  either during COLLECTINFORMATION or DISTRIBUTEINFORMATION,  $C_i$  absorbs information from  $C_j$ . Absorption of information involves performing the following calculations:

- (1) Calculate the updated separator potential:

$$\phi_S^* = \sum_{C_j \setminus S} \phi_{C_j}.$$

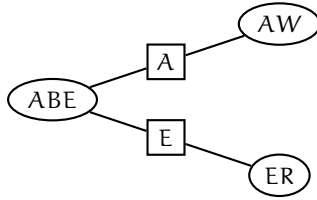
- (2) Update the clique potential of  $C_i$ :

$$\phi_{C_i} := \phi_{C_i} \frac{\phi_S^*}{\phi_S}.$$

- (3) Associate the updated potential with the separator:

$$\phi_S = \phi_S^*.$$

After a full round of message passing the potential associated with any clique (separator) is the joint probability distribution (up to the same normalization constant) of the variables in the clique (separator) and the evidence. This algorithm is known as the *Hugin algorithm*. Details on the inference process can be found in the literature (Lauritzen & Spiegelhalter 1988, Andersen, Olesen, Jensen & Jensen 1989, Jensen et al. 1990, Dawid 1992, Jensen et al. 1994, Lauritzen & Jensen 2001).



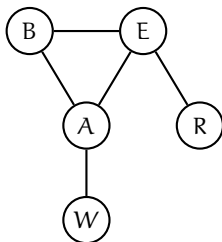
**Fig. 5.10.** A junction tree representation  $\mathcal{T}$  of the Bayesian network depicted in Figure 5.5 on page 115.

*Example 5.8.* Figure 5.10 shows a junction tree representation  $\mathcal{T} = (\mathcal{C}, \mathcal{S})$  of the Bayesian network depicted in Figure 5.5 on page 115 with cliques:

$$\mathcal{C} = \{\{A, B, E\}, \{E, R\}, \{A, W\}\}$$

and separators:

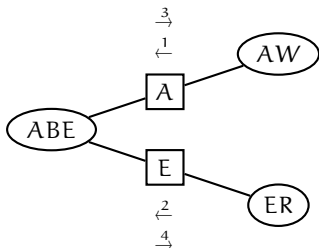
$$\mathcal{S} = \{\{E\}, \{A\}\}.$$



**Fig. 5.11.** The undirected graph corresponding to Figures 5.6, 5.7 and 5.10.

Notice the similarity between Figure 5.10 and Figures 5.6 and 5.7. The nodes of Figures 5.6 and 5.7 are clusters (i.e., subsets of variables) whereas the nodes of Figure 5.10 are cliques (i.e., maximal subsets of pairwise connected variables) of undirected graphs.

The undirected graph corresponding to a junction tree is obtained by adding undirected edges between each pair of variables contained in the same clique or cluster. Figure 5.11 is the undirected graph corresponding to Figures 5.6, 5.7 and 5.10.



**Fig. 5.12.** Message passing in  $\mathcal{T}$ .

Figure 5.12 shows how messages are passed over  $\mathcal{T}$  relative to the root ABE.

Underlying any approach to inference is the junction tree representation, although its presence may be implicit. Figure 5.6 shows the cluster tree representation underlying the computation of  $P(A)$  whereas Figure 5.7 shows the cluster tree representation underlying the computation of  $P(W)$ . Figures 5.6 and 5.7 are not junction trees, but cluster trees. The cliques of a junction tree are maximal complete subsets of pairwise connected variables, whereas clusters are not necessarily maximal.

The quality of the junction tree  $\mathcal{T} = (\mathcal{C}, \mathcal{S})$  determines the efficiency of inference. A common score or criterion to use when considering the optimality of a junction tree is the maximum state space size over all cliques in  $\mathcal{T}$ ,

i.e.,  $\max_{C \in \mathcal{C}} \|C\|$ . Another similar score is the sum over all cliques in  $\mathcal{T}$ , i.e.,  $\sum_{C \in \mathcal{C}} \|C\|$ .

All types of probabilistic networks considered in this book may be solved by message passing in a junction tree representation. However, we will restrict ourselves from a detailed treatment of this topic for all models presented as it is beyond the scope of this book.

The approach to inference outlined above may be referred to as an *indirect approach*.

### 5.1.2 Inference in CLG Bayesian Networks

Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{F})$  be a CLG Bayesian network with continuous random variables,  $\mathcal{X}_\Gamma$ , and discrete random variables,  $\mathcal{X}_\Delta$ , such that  $\mathcal{X} = \mathcal{X}_\Gamma \cup \mathcal{X}_\Delta$ . To solve the probabilistic inference task on  $\mathcal{N}$  is to compute the marginal for each  $X \in \mathcal{X}$ . Since  $\mathcal{N}$  is a CLG Bayesian network the task of performing inference becomes more subtle than in the case of a pure discrete Bayesian network.

The prior distribution,  $P(X)$ , of a discrete variable  $X \in \mathcal{X}_\Delta$  is equal to the distribution of  $X$  in the discrete network  $\mathcal{N}' = (\mathcal{X}_\Delta, \mathcal{P})$  obtained by removing all continuous variables from the model (all continuous variables are barren variables with respect to the joint over the discrete variables). The prior density of a continuous variable  $Y$ , on the other hand, will, in general, be a mixture of Gaussian distributions where the mixing factors are joint probabilities over configurations of discrete variables  $I \subseteq \mathcal{X}_\Delta$ . For each configuration  $\mathbf{i}$  of  $I$  with non-zero probability, i.e.,  $p(\mathbf{i}) > 0$ , the joint distribution of  $I$  and  $X$  has the form

$$P(I = \mathbf{i}) * \mathbb{N}(\mu(\mathbf{i}), \sigma^2(\mathbf{i})).$$

This implies that the marginal of  $X \in \mathcal{X}_\Gamma$  is

$$\mathcal{L}(X) = \sum_{\mathbf{i}: P(I=\mathbf{i}) > 0} P(\mathbf{i}) * \mathbb{N}(\mu(\mathbf{i}), \sigma^2(\mathbf{i})).$$

For each configuration  $\mathbf{i}$  of  $I$  with  $P(\mathbf{i}) = 0$  the mean  $\mu(\mathbf{i})$  and variance  $\sigma^2(\mathbf{i})$  may be random numbers. Hence, the marginal density function for a continuous variable  $X \in \mathcal{X}_\Gamma$  is, in general, a mixture of Gaussian distributions

$$f(x) = \sum_{i=0}^n \alpha_i f_i(x),$$

where each component  $f_i$  is a one-dimensional Gaussian density function in  $X$  and each coefficient  $\alpha_i$  is the probability of a configuration of discrete variables. This implies that the marginal density function of  $X \in \mathcal{X}_\Gamma$  is not necessarily a CLG distribution with the indicated mean  $\mu$  and variance  $\sigma^2$ . That is, the result of a marginalization of a CLG distribution over continuous variables

is a CLG distribution whereas the result of a marginalization of a CLG distribution over discrete variables, in general, is not. The first type of marginal is referred to as a *strong marginal*, whereas the latter is referred to as a *weak marginal*. The marginal is strong as we compute the mean  $\mu$  and the variance  $\sigma^2$ , and we know the distribution is a CLG distribution.

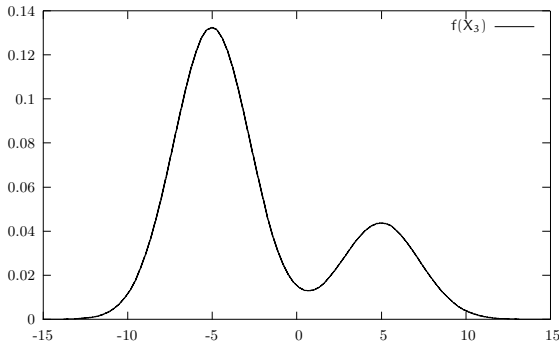
Probabilistic inference is the task of updating our belief about the state of the world in light of evidence. Evidence on discrete variables, be it hard or soft evidence, is treated as in the case of discrete Bayesian networks. Evidence on a continuous variable, on the other hand, is restricted to be hard evidence, i.e., instantiations.

In the general case where evidence  $\varepsilon$  is available, the marginal for a discrete variable  $X \in \mathcal{X}_\Delta$  is a probability distribution  $P(X|\varepsilon)$  conditional on the evidence  $\varepsilon$ , whereas the marginal for a continuous variable  $X \in \mathcal{X}_\Gamma$  is a density function  $f(x|\varepsilon)$  conditional on  $\varepsilon$  with a mean  $\mu$  and a variance  $\sigma^2$ .

*Example 5.9.* Example 4.3 on page 72 shows an example of a simple CLG Bayesian network. Computing the prior probability density in  $X_3$  amounts to eliminating the variables  $X_1$  and  $X_2$ . With the quantification specified in Example 4.3 this produces the following mixture

$$\mathcal{L}(X_3) = 0.75 * \mathcal{N}(-5, 5.1) + 0.25 * \mathcal{N}(5, 5.2)$$

with mean  $\mu = -2.5$  and variance  $\sigma^2 = 23.88$ . Notice that the density for  $X_3$  is not the density for the Gaussian distribution with mean  $\mu = -2.5$  and variance  $\sigma^2 = 23.88$ . The density function is shown in Figure 5.13.



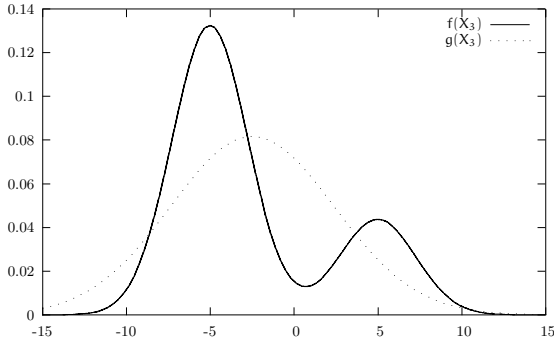
**Fig. 5.13.** The density function for  $X_3$ .

The prior probability density for  $X_2$  and the prior probability distribution for  $X_1$  are trivial to compute as  $\{X_2, X_3\}$  are barren with respect to the prior for  $X_1$  and similarly  $\{X_1, X_3\}$  are barren with respect to the prior for  $X_2$ .



The above examples illustrates that the class of CLG distributions is not closed under the operation of discrete variable elimination. The weak marginal distribution  $\mathcal{N}(\mu, \sigma^2)$  may, however, be used as an approximation of the *true* marginal. The weak marginal is the closest non-mixture to the true marginal in terms of the Kullback–Leibler distance (Lauritzen 1996).

*Example 5.10.* Consider again the CLG Bayesian network  $\mathcal{N}$  from Example 4.3 on page 72. Figure 5.13 on the preceding page shows the density function for  $X_3$ . Figure 5.14 shows both the density function  $f(X_3)$  and the weak mar-



**Fig. 5.14.** The density function  $f(X_3)$  for  $X_3$  and its weak marginal  $g(X_3)$ .

ginal  $g(X_3)$  for  $X_3$ . It is obvious that the weak marginal is only an approximation of the exact density function.

Since the CLG distribution is not closed under the operation of discrete variable elimination and since the operation of discrete variable elimination is not defined when continuous variables are in the domain of the potential to be marginalized, it is required that continuous variables are eliminated before discrete variables. For this reason, when marginalizing over both continuous and discrete variables, we first marginalize over the continuous variables and then over the discrete variables (Lauritzen 1992b).

This implies that the (exact) solution method for inference in CLG Bayesian networks induce the partial order  $\mathcal{X}_\Delta \prec \mathcal{X}_\Gamma$  on the elimination order. Hence, the continuous variables  $\mathcal{X}_\Gamma$  should be eliminated before the discrete variables  $\mathcal{X}_\Delta$ . A variable elimination order, which is restricted to induce a certain (partial) order, is referred to as a *strong* elimination order. Hence, we use a strong elimination order to solve a CLG Bayesian network by variable elimination. For this reason, inference in a CLG Bayesian network may be more resource intensive than inference in a corresponding Bayesian network with the same structure, but consisting only of continuous random variables. Notice that due to independence relations induced by the structure of  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$

of a CLG Bayesian network and the structure of the evidence  $\varepsilon$ , it may in some situations be possible to eliminate discrete variables before continuous variables.

In the special case where the ancestors of  $v \in V$  are all representing continuous variables (i.e.,  $\text{an}(v) \subseteq V_{\Gamma}$ ) for  $X_v \in \mathcal{X}$ , the posterior marginal for  $X_v$  is a strong marginal. Otherwise, it is a weak marginal. If the posterior for  $X_v$  is a weak marginal, the density function of  $X_v$  is an unknown mixture of Gaussians, which needs to be computed as part of probabilistic inference.

The normalization constant  $\alpha$  computed as part of probabilistic inference is proportional to the density at the observed values of the continuous variables. The proportionality constant is  $P(\varepsilon(\Delta) | \varepsilon(\Gamma))$ , where  $\varepsilon(\Delta)$  is the evidence on discrete variables and  $\varepsilon(\Gamma)$  is the evidence on continuous variables. In general,  $\alpha$  is scale-dependent and does not make much sense. For instance, the value of  $\alpha$  will be dependent on whether height is measured in meters or centimeters. If  $\varepsilon$  only contains discrete variables, then  $\alpha$  is the probability of  $\varepsilon$ .

The presence of both continuous and discrete variables makes the operations required for performing probabilistic inference in CLG Bayesian networks more complicated than those required for performing probabilistic inference in discrete Bayesian networks. For a detailed treatment on inference in CLG Bayesian networks, see for example Lauritzen (1992b) and Lauritzen & Jensen (2001).

## 5.2 Solving Decision Models

We build decision models in order to support efficient reasoning and decision making under uncertainty in a given problem domain. Reasoning under uncertainty is the task of computing our updated beliefs in (unobserved) events given observations on other events whereas decision making under uncertainty is the task of identifying the (optimal) decision strategy for the decision maker given observations.

### 5.2.1 Solving Discrete Influence Diagrams

Inference in an influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  is to determine an optimal strategy  $\hat{\Delta} = \{\hat{\delta}_1, \dots, \hat{\delta}_n\}$  for the decision maker and compute the maximum expected utility of adhering to  $\hat{\Delta}$ .

The influence diagram is a compact representation of a joint expected utility function due to the chain rule

$$\text{EU}(\mathcal{X}) = \prod_{X_v \in \mathcal{X}_C} P(X_v | X_{\text{pa}(v)}) \sum_{w \in V_U} u(X_{\text{pa}(w)}).$$

Applying the  $\sum$ -max- $\sum$ -rule (Jensen 1996) on the joint expected utility function, we may solve  $\mathcal{N}$  by eliminating variables in the reverse order of the

information precedence order  $\prec$ . That is, the precedence relation  $\prec$  induces a partial order on the elimination of variables in  $\mathcal{X}$ . This implies that we use a strong variable elimination order to solve an influence diagram by variable elimination.

Starting with the last decision  $D_n$ , the  $\sum$ -max- $\sum$ -rule says that we should average over the unknown random variables  $J_n$ , maximize over the decision  $D_n$ , average over the random variables  $J_{n-1}$  known to the decision maker at  $D_n$  (but not known to the analyst), maximize over  $D_{n-1}$ , and so on. The principle is to average over the unknown random variables, maximize over the decision variable, and finally average over the observed random variables.

The intuition behind the application of the  $\sum$ -max- $\sum$ -rule in reverse order of decisions is as follows. When we consider the last decision  $D_n$  its past is fully observed and the only unobserved variables are the variables never observed or observed after  $D_n$ , i.e.,  $J_n$ . Hence, after averaging over  $J_n$ , we can select a maximizing argument of the utility function  $u(J(D_n), D_n)$  for each configuration of  $J(D_n)$  as an optimal decision at  $D_n$ . Notice that we select a maximizing argument for each configuration of the past. In principle, this eliminates  $J_n$  and  $D_n$  from the decision problem and we may consider  $D_{n-1}$  as the last decision. This implies that when we solve for  $D_{n-1}$  we assume the decision maker to act optimally for  $D_n$ .

Notice that the variables are observed at the time of decision, but not (necessarily) at the time of analysis. Whether a random variable is known or unknown is defined from the point of view of the decision maker, and not the analyst. In this way we may solve  $\mathcal{N}$  by computing the maximum expected utility  $\text{MEU}(\hat{\Delta})$  of the optimal strategy  $\Delta$  as

$$\begin{aligned} \text{MEU}(\hat{\Delta}) &= \sum_{J_0} \max_{D_1} \sum_{J_1} \max_{D_2} \cdots \sum_{J_{n-1}} \max_{D_n} \sum_{J_n} EU(\mathcal{X}) \\ &= \sum_{J_0} \max_{D_1} \sum_{J_1} \max_{D_2} \cdots \sum_{J_{n-1}} \max_{D_n} \\ &\quad \prod_{X_v \in \mathcal{X}_c} P(X_v | X_{\text{pa}(v)}) \sum_{U_w \in \mathcal{X}_u} u(X_{\text{pa}(w)}). \end{aligned} \quad (5.8)$$

As part of the process, prior to the elimination of each decision  $D$ , we record the maximizing arguments of  $D$  over the utility potential  $\psi(D, J(D))$  from which  $D$  is eliminated for each configuration of  $J(D)$ . From  $\psi(D, J(D))$  we define the (probabilistic) policy function  $\delta(D | J(D))$  for  $D$  as

$$\delta(d | J(D) = i) = \begin{cases} 1 & \text{if } d = \arg \max_{d'} \psi(d', i), \\ 0 & \text{otherwise,} \end{cases}$$

where we assume the maximizing argument  $\arg \max_{d'} \psi(d', i)$  to be unique. If it is not unique, then any maximizing argument may be chosen.<sup>2</sup>

<sup>2</sup> As we shall see in Section 5.2.4, the policy function need not be deterministic.

*Example 5.11 (Oil Wildcatter).* To solve the decision problem of the Oil Wildcatter of Example 4.5 on page 77 is to identify the optimal decision policies for the test and drill decisions. From the joint expected utility function,  $EU(\mathcal{X})$ , over variables  $\mathcal{X}$  of  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$ , we may compute the maximum expected utility,  $MEU(\hat{\Delta})$ , of the optimal strategy,  $\hat{\Delta} = \{\hat{\delta}_D(S, T), \hat{\delta}_T()\}$ , and in the process determine the optimal strategy as

$$MEU(\hat{\Delta}) = \max_T \sum_S \max_D \sum_O P(O)P(S|O, T)(C(T) + U(D, O)).$$

Table 5.1 shows the expected utility function over  $D, S, T$  from which the decision policy  $\hat{\delta}_D(S, T)$  is identified as the maximizing argument of  $D$  for each configuration of  $S$  and  $T$ . The oil wildcatter should drill for oil unless he performed the test and obtained a diffuse pattern.

D	S	T	
no	cl	no	0
yes	cl	no	7
no	op	no	0
yes	op	no	7
no	di	no	0
yes	di	no	7
no	cl	yes	-2.4
yes	cl	yes	18.6
no	op	yes	-3.5
yes	op	yes	8
no	di	yes	-4.1
yes	di	yes	-16.6

**Table 5.1.** The joint expected utility function  $EU(D, S, T)$ .

Table 5.2 shows the expected utility function over  $T$  from which the decision policy  $\hat{\delta}_T()$  is identified as the maximizing argument of  $T$ . Hence, the test should always be performed.

T	
no	21
yes	22.5

**Table 5.2.** The expected utility function  $EU(T)$ .

The decision policies  $\hat{\delta}_T()$  and  $\hat{\delta}_D(S, T)$  are already known from Example 4.7 on page 79. The maximum expected utility for the decision problem is 22.5.

Solving an influence diagram by performing the variable eliminations according to Equation 5.8 will be highly inefficient even for simple influence diagrams. Instead we will — as in the case of Bayesian networks — apply a generalized version of the distributive law to increase computational efficiency.

For notational convenience, the generalized marginalization operator  $\bigvee$  was introduced by Jensen et al. (1994). The marginalization operator works differently for marginalization of random variables and decision variables:

$$\bigvee_X \rho \triangleq \sum_X \rho \quad \text{and} \quad \bigvee_D \rho \triangleq \max_D \rho,$$

where  $X$  is a random variable while  $D$  is a decision variable. We will use the generalized marginalization operator to explain the process of solving an influence diagram, see Madsen & Jensen (1999) for details.

Using a generalized version of the distributive law, the solution of an influence diagram may proceed as follows. Let  $Y$  be the first random variable to eliminate. The set of utility potentials  $\mathcal{U}$  can be divided into two disjoint subsets with respect to  $Y$ . Let  $\mathcal{U}_Y \subseteq \mathcal{U}$  be the subset of utility potentials including  $Y$  in the domain

$$\mathcal{U}_Y = \{u \in \mathcal{U} | Y \in \text{dom}(u)\}.$$

Then  $\mathcal{U} \setminus \mathcal{U}_Y$  is the set of utility potentials not including  $Y$  in the domain. Similarly, let  $\mathcal{P}_Y \subseteq \mathcal{P}$  be the subset of probability distributions including  $Y$  in the domain

$$\mathcal{P}_Y = \{P \in \mathcal{P} | Y \in \text{dom}(P)\}.$$

Then  $\mathcal{P} \setminus \mathcal{P}_Y$  is the set of probability potentials not including  $Y$  in the domain. The elimination process proceeds by local computation in order to maintain efficiency (i.e., we exploit the distributive law to maintain the factorization of the joint expected utility function). Let  $\phi_Y$  be the probability potential obtained by eliminating  $Y$  from the combination of all probability potentials in  $\mathcal{P}_Y$  and let  $\psi_Y$  be the utility potential obtained by eliminating  $Y$  from the combination of all probability and utility potentials in  $\mathcal{P}_Y \cup \mathcal{U}_Y$  such that

$$\begin{aligned} \phi_Y &= \bigvee_Y \prod_{\phi \in \mathcal{P}_Y} \phi, \\ \psi_Y &= \bigvee_Y \phi_Y \sum_{\psi \in \mathcal{U}_Y} \psi. \end{aligned} \tag{5.9}$$

The two potentials  $\phi_Y$  and  $\psi_Y$  will be used to enforce the factorization of the joint expected utility function over  $\mathcal{X} \setminus \{Y\}$ . The factorization may be achieved by rewriting Equation 5.8 using  $\phi_Y$  and  $\psi_Y$  as well as applying the distributive law

$$\begin{aligned}
\text{MEU}(\hat{\Delta}) &= \bigvee_{X \in \mathcal{X}} \left( \prod_{\phi \in \mathcal{P}} \phi \sum_{\psi \in \mathcal{U}} \psi \right) \\
&= \bigvee_{X \in \mathcal{X}} \left[ \left( \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi \prod_{\phi' \in \mathcal{P}_Y} \phi' \right) \left( \sum_{\psi \in \mathcal{U} \setminus \mathcal{U}_Y} \psi + \sum_{\psi' \in \mathcal{U}_Y} \psi' \right) \right] \\
&= \bigvee_{X \in \mathcal{X} \setminus \{Y\}} \left[ \left( \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi \right) \bigvee_Y \left( \prod_{\phi' \in \mathcal{P}_Y} \phi' \right) \left( \sum_{\psi \in \mathcal{U} \setminus \mathcal{U}_Y} \psi + \sum_{\psi' \in \mathcal{U}_Y} \psi' \right) \right] \\
&= \bigvee_{X \in \mathcal{X} \setminus \{Y\}} \left[ \left( \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi \right) \left( \left( \sum_{\psi \in \mathcal{U} \setminus \mathcal{U}_Y} \psi \right) \phi_Y + \psi_Y \right) \right] \quad (5.10)
\end{aligned}$$

$$= \bigvee_{X \in \mathcal{X} \setminus \{Y\}} \left[ \left( \prod_{\phi \in \mathcal{P} \setminus \mathcal{P}_Y} \phi \right) \phi_Y \left( \sum_{\psi \in \mathcal{U} \setminus \mathcal{U}_Y} \psi + \frac{\psi_Y}{\phi_Y} \right) \right]. \quad (5.11)$$

Equation 5.11 specifies a decomposition of the joint expected utility function over  $\mathcal{X} \setminus \{Y\}$ , and decomposition has the form of Equation 5.8. The decomposition is the product of the summation over the elements of  $\mathcal{U} \setminus \mathcal{U}_Y \cup \{\frac{\psi_Y}{\phi_Y}\}$  and the product over the elements of  $\mathcal{P} \setminus \mathcal{P}_Y \cup \{\phi_Y\}$ . In addition, we have performed the elimination of  $Y$  by local computations only involving potentials with  $Y$  as a domain variable. We say that the sets

$$\mathcal{P} \setminus \mathcal{P}_Y \cup \{\phi_Y\} \quad \text{and} \quad \mathcal{U} \setminus \mathcal{U}_Y \cup \left\{ \frac{\psi_Y}{\phi_Y} \right\},$$

are a value preserving reduction of  $\mathcal{P}$  and  $\mathcal{U}$  where  $Y$  has been eliminated. The elimination of the next variable may proceed in the same manner on  $\mathcal{U} \setminus \mathcal{U}_Y \cup \{\frac{\psi_Y}{\phi_Y}\}$  and  $\mathcal{P} \setminus \mathcal{P}_Y \cup \{\phi_Y\}$ .

The division operation in Equation 5.11 is introduced because the combination of probability potentials and utility potentials is non-associative. Thus, either the division should be performed or the probability potentials have to be distributed over the terms of the utility function as in Equation 5.10.

*Example 5.12 (Oil Wildcatter).* Utilizing the local computation approach explained above we may solve the Oil Wildcatter problem as follows

$$\begin{aligned}
\text{EU}(\hat{\Delta}) &= \max_T \sum_S \max_D \sum_O P(O)P(S|O, T)(C(T) + U(D, O)) \\
&= \max_T (C(T) + \sum_S P(S) \max_D \sum_O \frac{P(O)P(S|O, T)}{P(S)} U(D, O)).
\end{aligned}$$

The division by  $P(S)$  is necessary in order to obtain the correct conditional expected utility for  $D$ . This division does not effect the policy.

The benefit of the local computation approach is more profound on large and more complex influence diagrams.

### 5.2.2 Solving CLQG Influence Diagrams

Inference in a CLQG influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{F}, \mathcal{U})$  is similar to inference in a discrete influence diagram. The task is to determine an optimal strategy,  $\hat{\Delta} = \{\hat{\delta}_1, \dots, \hat{\delta}_n\}$ , for the decision maker and compute the maximum expected utility of adhering to  $\hat{\Delta}$ .

The influence diagram is a compact representation of a joint expected utility function due to the chain rule

$$\text{EU}(\mathcal{X}_{\Delta} = \mathbf{i}, \mathcal{X}_{\Gamma}) = \prod_{v \in V_{\Delta}} P(i_v | i_{\text{pa}(v)}) * \prod_{w \in V_{\Gamma}} p(y_w | X_{\text{pa}(w)}) * \sum_{z \in V_{\mathcal{U}}} u(X_{\text{pa}(z)}).$$

The solution process for CLQG influence diagrams follows the same approach as the solution process for discrete influence diagrams. The solution process proceeds by applying an extension of the  $\sum$ -max- $\sum$ -rule (Madsen & Jensen 2005). The extension is that we need to eliminate the continuous random variables  $\mathcal{X}_{\Gamma}$  by integration as opposed to summation. We refer the interested reader to the literature for details on the solution process (Kenley 1986, Shachter & Kenley 1989, Poland 1994, Madsen & Jensen 2005).

The optimal strategy  $\hat{\Delta} = \{\hat{\delta}_1, \dots, \hat{\delta}_n\}$  will consist of decision policies for both discrete and continuous decision variables. The decision policy for a discrete decision variable  $D_i \in \mathcal{X}_{\Delta} \cap \mathcal{X}_{\mathcal{D}}$  is a mapping from the configuration of its past  $\mathcal{I}(D_i)$  to  $\text{dom}(D_i)$ , whereas the decision policy for a continuous decision variable  $D_j \in \mathcal{X}_{\Gamma} \cap \mathcal{X}_{\mathcal{D}}$  is a multi-linear function in its continuous past  $\mathcal{I}(D_i) \cap \mathcal{X}_{\Gamma}$  conditional on its discrete past  $\mathcal{I}(D_i) \cap \mathcal{X}_{\Delta}$ .

*Example 5.13 (Marketing Budget (Madsen & Jensen 2005)).* Consider a company manager has to decide on a unit price, **Price**, to charge for a certain item she wants to sell. The number of items sold, **Units**, is a function of the price and marketing budget, **Budget**, whereas the cost of production, **Cost**, is a function of the number of items sold. This scenario can be modeled using the CLQG influence diagram shown in Figure 5.15 on the following page. Prior to making the decision on price she will be allocated a marketing budget.

The decision problem may be quantified as follows where the unit of utility is thousands of euros. The distributions of items sold and production cost are

$$\begin{aligned} \mathcal{L}(\text{Units} | \text{Budget} = b, \text{Price} = p) &= \mathbb{N}(20 + 0.2 * b - 0.1 * p, 25) \\ \mathcal{L}(\text{Cost} | \text{Units} = u) &= \mathbb{N}(400 + 10 * u, 2500) \end{aligned}$$

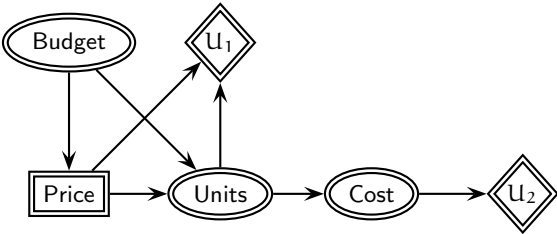
The distribution of marketing budget is

$$\mathcal{L}(\text{Budget}) = \mathbb{N}(100, 400).$$

The cost function is

$$U_2(\text{Cost} = c) = -c$$

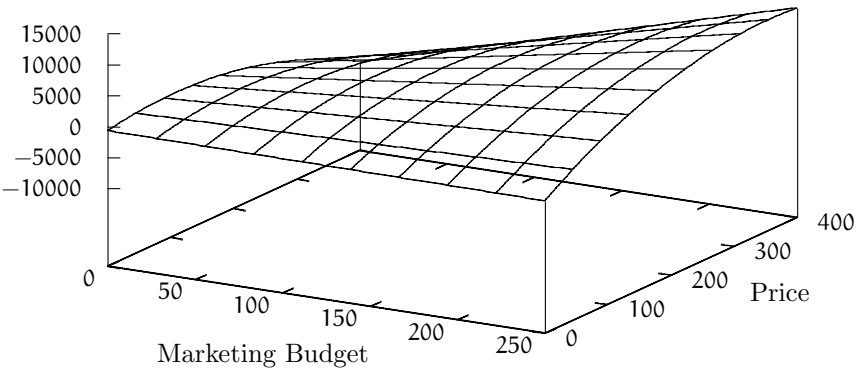
and the revenue function is



**Fig. 5.15.** Optimization of price given marketing budget size.

$$U_1(\text{Price} = p, \text{Units} = u) = u * p.$$

Figure 5.16 shows the expected utility function as a function of  $M$  and  $P$ . The optimal decision policy  $\delta_P(m)$  for  $P$  is a linear function in  $M$ :  $\delta_P(m) = 105 + m$ .



**Fig. 5.16.** Expected utility as a function of price and marketing budget.

**5.2.3 Relevance Reasoning**

As mentioned in the previous section, a policy  $\delta$  for  $D$  is a mapping from past observations and decisions to the possible decision options at  $D$ . When



modeling a large and complex decision problem involving a sequence of decisions, the past observations and decisions of a decision may involve a large set of variables. At the same time, it may be that only a small subset of these are essential for the decision. Informally speaking, an observation (or decision) is essential (also known as *requisite*) for a decision, if the outcome of the observation may impact the choice of decision option.

Assume we are able to identify and remove non-requisite parents of each decision. This makes a policy for decision  $D$  a function from the requisite past  $RP(D)$  to the decision options such that  $\delta : RP(D) \rightarrow \text{dom}(D)$ . It is not a trivial task to determine the requisite past of a decision  $D$ , i.e., the variables observed prior to  $D$ , whose values have an impact on the choice of decision option for  $D$  (Shachter 1998, Lauritzen & Nilsson 2001, Nielsen 2001).

**Definition 5.4 (Requisite Observation).** *Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G} = (V, E), \mathcal{P}, \mathcal{U})$  be an influence diagram. The observation on variable  $Y_v \in \mathcal{J}(D_i)$  is requisite for decision  $D_i$  in  $\mathcal{N}$  if and only if  $v \not\perp_{\mathcal{G}} \bigvee_{\mathcal{U}} \bigcap \text{de}(v_i) \mid (V_{\mathcal{J}(D_i)} \setminus \{v\})$ , where  $v_i$  is the node representing  $D_i$ .*

The solution algorithm will identify some of the non-requisite parents for each decision, but there is no guarantee that all non-requisite parents will be identified and ignored. The implicit identification of non-requisite parents is due to conditional independence properties of the graph.

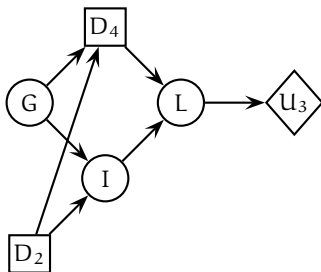
Similar to the concept of a requisite observation is the concept of a *relevant variable*. The set of variables relevant for a decision,  $D$ , is the set of variables observed and the set of decisions made after decision  $D$ , which may impact the expected utility of  $D$ .

**Definition 5.5 (Relevant Variable).** *Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G} = (V, E), \mathcal{P}, \mathcal{U})$  be an influence diagram. A variable  $Y_v \in \mathcal{F}(D_i)$  is relevant for decision  $D_i$  if and only if  $v \not\perp_{\mathcal{G}} \bigvee_{\mathcal{U}} \bigcap \text{de}(v_i) \mid (V_{\mathcal{J}(D_i)} \setminus \{v\})$ , where  $v_i$  is the node representing  $D_i$ .*

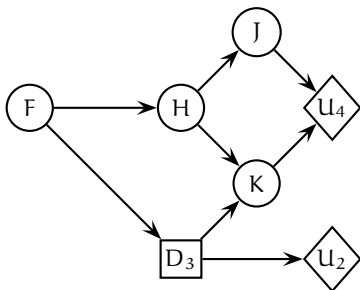
Using the concepts of relevant variables and requisite observations it is possible to decompose the structure of an influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G} = (V, E), \mathcal{P}, \mathcal{U})$  into a sub-models consisting only of requisite parents and relevant variables for each decision in  $\mathcal{N}$ .

*Example 5.14 (Decomposition of Influence Diagrams (Nielsen 2001)).* Consider the influence diagram shown in Figure 4.10 on page 84. Traversing the decision variables in reverse order, we may for each decision variable construct the sub-model consisting of relevant variables and requisite parents only.

We consider the decisions in reverse order starting with  $D_4$ . The reasoning proceeds by searching for non-requisite parents of  $D_4$ . By inspection of the diagram it becomes clear that  $G$  blocks the flow of information from observations made prior to  $D_4$  to the only utility descendant  $U_3$  of  $D_4$ . Hence, all other parents are non-requisite. Similarly, we identify the set of relevant variables. Figure 5.17 on the following page shows the DAG induced by the subset of requisite observations and relevant variables for  $D_4$ .

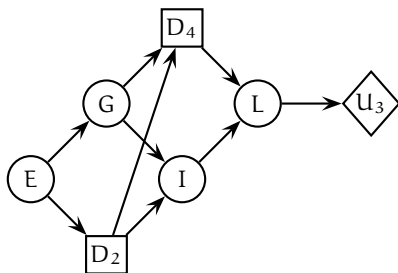


**Fig. 5.17.** The DAG induced by the subset of requisite observations and relevant variables for D<sub>4</sub>.



**Fig. 5.18.** The DAG induced by the subset of requisite observations and relevant variables for D<sub>3</sub>.

Similarly, Figure 5.18 and Figure 5.19 show the DAGs induced by the subsets of requisite observations and relevant variables for D<sub>3</sub> and D<sub>2</sub>, respectively.



**Fig. 5.19.** The DAG induced by the subset of requisite observations and relevant variables for D<sub>2</sub>.

The DAG induced by the subset of requisite observations and relevant variables for  $D_1$  is equal to the DAG shown in Figure 4.10 on page 84.

Decomposing an influence diagram into its sub-models of requisite observations and relevant variables for each decision is very useful for model validation.

### 5.2.4 Solving LIMIDs

The LIMID representation relaxes the two fundamental assumptions of the influence diagram representation. The assumptions are the total order on decisions and the perfect recall of past decisions and observations. These two assumptions are fundamental to the solution algorithm for influence diagrams described above. Due to the relaxation of these two assumptions, the solution process of LIMIDs becomes more complex than the solution process of influence diagrams.

Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  be a LIMID representation of a decision problem. The *Single Policy Updating* (SPU) algorithm is an iterative procedure for identifying (locally) optimal decision policies for the decisions of  $\mathcal{N}$ . The basic idea is to start an iterative process from some initial strategy where the policy at each decision is updated while keeping the remaining policies fixed until convergence. The starting point can be the uniform strategy where all options are equally likely to be chosen by the decision maker.

As mentioned in Chapter 4, a decision policy  $\delta_{D_i}$  is a mapping from the decision past of  $D_i$  to the state space  $\text{dom}(D_i)$  of  $D_i$  such that  $\delta_{D_i}: \mathcal{J}(D_i) \rightarrow \text{dom}(D_i)$ . This implies that we may use the probabilistic policy function  $\delta'_i(D_i | \mathcal{J}(D_i))$  of  $\delta_{D_i}(\mathcal{J}(D_i))$  introduced in Section 5.2.1

$$\delta'_i(d_i | \mathcal{J}(D_i) = j) = \begin{cases} 1 & \text{if } d_i = \delta_{D_i}(j), \\ 0 & \text{otherwise.} \end{cases}$$

This encoding will play a central role in the process of solving a LIMID.

Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  be a LIMID model with chance and decision variables  $\mathcal{X}_C$  and  $\mathcal{X}_D$ , respectively. A strategy  $\Delta = \{\delta_D : D \in \mathcal{X}_D\}$  for  $\mathcal{N}$  induces a joint probability distribution  $P_\Delta(\mathcal{X})$  over  $\mathcal{X}$  as it specifies a probability distribution for each decision variable:

$$P_\Delta(\mathcal{X}) = \prod_{X_v \in \mathcal{X}_C} P(X_v | X_{\text{pa}(v)}) \prod_{D_i \in \mathcal{X}_D} \delta'_i. \quad (5.12)$$

The aim of solving  $\mathcal{N}$  is to identify a strategy,  $\Delta$ , maximizing the expected utility

$$EU(\Delta) = \sum_{\mathcal{X} \in \mathcal{X}} P_\Delta(\mathcal{X}) \mathcal{U}(\mathcal{X}) = \prod_{X_v \in \mathcal{X}_C} P(X_v | X_{\text{pa}(v)}) \prod_{D_i \in \mathcal{X}_D} \delta'_i \sum_{\mathcal{U} \in \mathcal{U}} \mathcal{U}.$$

The SPU algorithm starts with some initial strategy and iteratively updates a single policy until convergence has occurred. Convergence has occurred when no single policy modification can increase the expected utility of the strategy. As mentioned above, a common initial strategy is the uniform strategy  $\bar{\Delta} = \{\bar{\delta}_1', \dots, \bar{\delta}_n'\}$  consisting of uniform policies  $\bar{\delta}_1', \dots, \bar{\delta}_n'$  where  $\bar{\delta}_i'(d) = \frac{1}{\|\mathcal{D}_i\|}$  for each  $d \in \text{dom}(\mathcal{D}_i)$  and each  $\mathcal{D}_i \in \mathcal{X}_D$ .

Assume  $\Delta$  is the current strategy and  $\mathcal{D}_i$  is the next decision to be considered for a policy update, then SPU proceeds by performing the following steps

Retract Retract the policy  $\delta_i'$  from  $\Delta$  to obtain  $\Delta_{-i} = \Delta \setminus \{\delta_i'\}$  (i.e.,  $\Delta_{-i}$  is a strategy for all decisions except  $\mathcal{D}_i$ ).

Update Identify a new policy  $\hat{\delta}_i$  for  $\mathcal{D}_i$  by computing

$$\hat{\delta}_i = \arg \max_{\delta_i'} \text{EU}(\Delta_{-i} \cup \{\delta_i'\}).$$

Replace Set  $\Delta = \Delta_{-i} \cup \{\hat{\delta}_i\}$ .

SPU may consider the decisions in an arbitrary order. However, if the graph  $\mathcal{G}$  specifies a partial order on a subset of decisions  $\mathcal{D}_{i_1} \prec \dots \prec \mathcal{D}_{i_j} \prec \dots \prec \mathcal{D}_{i_m}$ , then these decisions are processed in reverse order, cf. the solution process of ordinary influence diagrams.

*Example 5.15 (Solving Breeding Pigs).* To solve the breeding pigs decision problem of Example 4.13 on page 90 is to identify a strategy consisting of one policy for each decision on whether or not to treat each pig for the disease. Using the SPU algorithm described above we may solve the decision problem by iteratively updating each single policy until convergence has occurred.

The uniform strategy will serve as the initial strategy. Hence, we assign a uniform policy  $\bar{\delta}_i$  to each decision  $\mathcal{D}_i$ . As there is a total temporal order on the decisions, we consider them in reverse temporal order.

The SPU algorithm updates the policy of each decision iteratively until convergence. Once convergence has occurred, we have obtained the strategy  $\Delta = \{\delta_{\mathcal{D}_1}, \delta_{\mathcal{D}_2}, \delta_{\mathcal{D}_3}\}$ , where

$$\delta_{\mathcal{D}_1}(R_1) = \begin{cases} \text{no} & R_1 = \text{unhealthy} \\ \text{no} & R_1 = \text{healthy} \end{cases}$$

$$\delta_{\mathcal{D}_2}(R_2) = \begin{cases} \text{yes} & R_2 = \text{unhealthy} \\ \text{no} & R_2 = \text{healthy} \end{cases}$$

$$\delta_{\mathcal{D}_3}(R_3) = \begin{cases} \text{yes} & R_3 = \text{unhealthy} \\ \text{no} & R_3 = \text{healthy} \end{cases}$$

For  $R_2$  and  $R_3$  the strategy is to treat a pig when the test indicates that the pig is unhealthy. For  $R_1$  no treatment should be performed. Notice that each policy is only a function of the most recent test result. This implies that previous results and decisions are ignored.

## Probability of Future Decisions

Equation 5.12 specifies a factorization of the joint probability distribution  $P_\Delta$  over  $\mathcal{X}$  encoded by a strategy  $\Delta$ . This factorization may be interpreted as a Bayesian network model. With this interpretation we are able to compute the probability of future events under the assumption that the decision maker adheres to the strategy  $\Delta$ . This property also holds for ordinary influence diagrams.

*Example 5.16 (Breeding Pigs).* In Example 5.15 we identified a strategy  $\Delta = \{\delta_{D_1}, \delta_{D_2}, \delta_{D_3}\}$  for the Breeding Pigs problem. Having identified a strategy, the farmer may be interested in knowing the probability of a pig being healthy when it is sold for slaughtering. This probability may be computed using Equation 5.12.

The probability of a pig being healthy under strategy  $\Delta$  is  $P_\Delta(H_4 = \text{true}) = 67.58$  whereas the probability of a pig being healthy under the uniform strategy  $\bar{\Delta}$  is  $P_{\bar{\Delta}}(H_4 = \text{true}) = 70.55$ . The uniform strategy has a lower maximum expected utility though.

## Minimal LIMIDs

LIMIDs relax the assumption of perfect recall of the decision maker. This implies that the structure of a LIMID defines what information is available to the decision maker at each decision. In addition to specifying what information is available to the decision maker, we may perform an analysis of which information is relevant to each decision.

It is not always obvious which informational links to include in a LIMID with graph  $\mathcal{G} = (V, E)$ . Sometimes a link  $(v, w) \in E$  from  $X_v \in \mathcal{X}_C$  to  $D_w \in \mathcal{X}_D$  may be removed from the graph  $\mathcal{G}$  without affecting the policies and the expected utility of the computed policies. When this is the case, we say that the link  $(v, w)$  (and the parent  $X_v$  given by the link) is non-requisite for  $D_w$ .

Removing all non-requisite informational links from a LIMID  $\mathcal{N} = (\mathcal{X}, \mathcal{G} = (V, E), \mathcal{P}, \mathcal{U})$  produces the minimal reduction  $\mathcal{N}^{\min} = (\mathcal{X}, \mathcal{G} = (V, E^*), \mathcal{P}, \mathcal{U})$  of  $\mathcal{N}$ . Any LIMID  $\mathcal{N}$  has a unique minimal reduction  $\mathcal{N}^{\min}$  obtained by iterative removal of informational links from non-requisite parents into decisions.

Since removing a non-requisite parent  $X$  from decision  $D_i$  may make another previously requisite parent  $Y \in X_{\text{pa}(v_i)}$  a non-requisite parent, it is necessary to iteratively process the parent set of each decision until no non-requisite parents are identified. If  $\mathcal{N}$  is an ordinary influence diagram, it is sufficient to perform a single pass over the decisions starting with the last

decision first. The reason is that we have a total order on the decisions and all decisions are extremal (see Definition 5.6 below).

### Optimal Strategies

In order to characterize the conditions under which SPU is guaranteed to find an optimal solution we need to define the notion of an *extremal decision*.

**Definition 5.6 (Extremal Decision).** *Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  be a LIMID. A decision variable  $D_i$  is extremal if and only if*

$$(\bigvee_{\mathcal{U}} \cap \text{de}(D_i)) \perp_{\mathcal{G}} \bigcup_{j \neq i} \text{fa}(D_j) | \text{fa}(D_i).$$

That is, a decision variable is extremal if all other decisions and their parents are d-separated from the utility descendants of  $D_i$  given the family of  $D_i$ .

A LIMID is *soluble* if all decisions are extremal. If  $D_i$  is extremal in  $\mathcal{N}$ , then it has an optimal policy. If all policies in  $\Delta$  are optimal, then  $\Delta$  is an optimal strategy.

*Example 5.17 (Breeding Pigs).* The Breeding Pigs network in Figure 4.15 on page 91 is not soluble as all decisions are non-extremal. This implies that the local optimal strategy identified is not necessarily a globally optimal strategy.

Similarly, Figure 4.14 of Example 4.12 on page 90 shows an example of a non-soluble LIMID  $\mathcal{N} = (\mathcal{X}, \mathcal{G} = (\mathcal{V}, \mathcal{E}), \mathcal{P}, \mathcal{U})$ . On the other hand, the LIMID  $\mathcal{N} = (\mathcal{X}, \mathcal{G} = (\mathcal{V}, \mathcal{E} \setminus \{(D_i, D_j)\}), \mathcal{P}, \mathcal{U})$  is soluble as both  $D_i$  and  $D_j$  are extremal.

Notice that since any ordinary influence diagram may be represented as a limited memory influence diagram, the SPU solution process may be used to solve influence diagrams, see e.g. Madsen & Nilsson (2001). Any ordinary influence diagram is a special case of a limited memory influence diagram. The LIMID representation of an ordinary influence diagram will produce an optimal strategy.

See Lauritzen & Nilsson (2001) for more details on the solution process.

### 5.3 Solving OOPNs

For the purpose of inference, an object-oriented model is unfolded. The unfolded network is subsequently transformed into the computational structure used for inference. This implies that to solve an object-oriented model is equivalent to solving its unfolded network. Hence, from the point of view of inference there is no difference between an object-oriented network and a flat network.

## 5.4 Summary

In this chapter we have considered the process of solving probabilistic networks. As the exact nature of solving a query against a probabilistic network depends on the type of model, the solution processes of Bayesian networks and influence diagrams have been considered separately.

We build Bayesian network models in order to support efficient reasoning under uncertainty in a given domain. Reasoning under uncertainty is the task of computing our updated beliefs in (unobserved) events given observations on other events, i.e., evidence.

We have considered the task of computing the posterior marginal of each unobserved variable,  $Y$ , given a (possibly empty) set of evidence  $\varepsilon$ , i.e.,  $P(Y|\varepsilon)$ . We have focused on the solution process that computes the posterior marginal for all unobserved variables using a two-phase message passing process on a junction tree structure.

We build decision models in order to support efficient reasoning and decision making under uncertainty in a given problem domain. Reasoning under uncertainty is the task of computing our updated beliefs in (unobserved) events given observations on other events whereas decision making under uncertainty is the task of identifying the (optimal) decision strategy for the decision maker given observations.

We have derived a method for solving influence diagrams by variable elimination. In the process of eliminating variables we are able to identify the decision policy for each decision. The resulting set of policies is the optimal strategy for the influence diagram.

The LIMID representation relaxes the two fundamental assumptions of the influence diagram representation. The assumptions are the total order on decisions and the perfect recall of past decisions and observations. These two assumptions are fundamental to the solution algorithm for influence diagrams described above. Due to the relaxation of these two assumptions, the solution process of LIMIDs becomes more complex than the solution process of influence diagrams.

We have described how the single policy updating algorithm iteratively identifies a set of locally optimal decision policies. A decision policy is globally optimal when the decision is extremal.

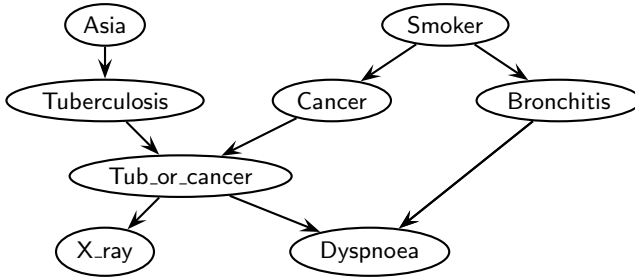
Finally, an OOPN is solved by solving its equivalent unfolded network.

## Exercises

**Exercise 5.1.** You are confronted with three doors, A, B, and C. Behind exactly one of the doors there is a big prize. The money is yours if you choose the correct door. After you have made your first choice of door but still not opened it, an official opens another one with nothing behind it, and you are allowed to alter your choice.

- (a) Construct a model for reasoning about the location of the prize.
- (b) Compute by hand the probability distribution over the location of the prize given you select door A and the official opens door B.

**Exercise 5.2.** Consider the Asia network shown in Figure 5.20 (see Example 4.2 on page 68 for more details).



**Fig. 5.20.** A graph specifying the independence and dependence relations of the Asia example.

- (a) Determine the set of barren variables for queries
 
$$Q_1 = (\mathcal{N}, \{\text{Bronchitis}\}, \{\}),$$

$$Q_2 = (\mathcal{N}, \{\text{Bronchitis}\}, \{\text{Dyspnoea} = \text{yes}\}),$$

$$Q_3 = (\mathcal{N}, \{\text{Bronchitis}\}, \{\text{Dyspnoea} = \text{no}, \text{X\_ray} = \text{yes}\}),$$
 where  $Q_i = (\mathcal{N}, \mathcal{T}, \varepsilon)$  with  $\mathcal{N}$  denoting the model,  $\mathcal{T}$  the target, and  $\varepsilon$  the evidence set.
- (b) Determine the set of nuisance variables for the same queries.

**Exercise 5.3.** Consider again the Asia network shown in Figure 5.20.

- (a) Identify the domain of potentials created by the elimination sequence  $\sigma = (\text{Tub\_or\_cancer}, \text{Asia}, \text{Smoker}, \text{Bronchitis}, \text{Cancer}, \text{X\_ray}, \text{Dyspnoea}, \text{Tuberculosis})$ .
- (b) Construct a junction tree representation using the elimination order  $\sigma$ .
- (c) Compare the answer to (a) with Figure 5.8 on page 117.

**Exercise 5.4.** Consider the influence diagram in Figure 4.10 on page 84.

- (a) Which variables are relevant for each decision node?
- (b) Which observed variables are requisite for each decision node?
- (c) Identify the partial order of the chance nodes relative to the decision nodes.
- (d) Identify the domains of each decision policy.

**Exercise 5.5.** Interpret the graph in Figure 4.10 on page 84 as a LIMID.



- (a) Identify the domains of decision policies and compare the results with the policies identified in Exercise 5.4(d).
- (c) Are any of the decision nodes extreme?

**Exercise 5.6.** Consider the decision problem in Exercise 5.1.

- (a) Calculate the MEU for the first choice/decision.
- (b) Explain the results of your calculations.
- (c) Construct an influence diagram for this problem, and check if the results are consistent with your calculations.
- (d) What is the optimal policy?

## **Model Construction**

## Eliciting the Model

A probabilistic network can be constructed manually, (semi-)automatically from data, or through a combination of a manual and a data driven process. In this chapter we will focus exclusively on the manual approach. See Chapter 8 for approaches involving data.

Faced with a new problem, one first has to figure out whether or not probabilistic networks are the right choice of “tool” for solving the problem. Depending on the nature of the problem, probabilistic networks might or might not be a natural choice of modeling methodology. In Section 6.1 we consider criteria to be fulfilled for probabilistic networks to be a suitable modeling methodology.

A probabilistic network consists of two components: structure and parameters (i.e., conditional probabilities and utilities (statements of preference)). The structure of a probabilistic network is often referred to as the qualitative part of the network, whereas the parameters are often referred to as its quantitative part. As the parameters of a model are determined by its structure, the model elicitation process always proceeds in two consecutive stages: First, the variables and the causal, functional or informational relations among the variables are identified, providing the qualitative part of the model. Second, once the model structure has been determined through an iterative process involving testing of variables and conditional independences, and verification of the directionality of the links, the values of the parameters are elicited.

Manual construction of probabilistic networks can be a labor-intensive task, requiring a great deal of skill and creativity as well as close communication with problem domain experts. Two key problems need to be addressed in the process of establishing the model structure: identification of the relevant variables and identification of the links between the variables.

The notion of variables (be they discrete chance or decision variables or continuous chance or decision variables) plays a key role in probabilistic networks. At a first glance it might seem like a relatively simple task to identify the variables of a probabilistic network, but experience shows that this might be a difficult task. In Section 6.2 we carefully introduce the notion of variables,

discuss the various types of variables and their roles, and provide a test that each variable should be able to pass.

In Section 6.3 we discuss the process of eliciting the structure of a probabilistic network for a problem domain, discussing both a basic approach, utilizing variable classification and typical causal relations among these, and a more elaborate approach based on identification of archetypical semantical substructures.

Although the use of structured approaches to elicitation of model structure might drastically reduce the risk of misplacing and/or reversing links, model verification ought to be performed before elicitation of model parameters is initiated. In Section 6.4 we discuss the importance of inspecting the model structure to verify that the dependence and independence properties encoded in the structure are reasonable.

Having the structure of the probabilistic network in place, the parameters (conditional probabilities and the utilities (if any)) of the network are identified. Quite often this is the most labor-intensive task, as the number of parameters can be counted in hundreds or even thousands, possibly each requiring consultation of a domain expert. In Section 6.5 we consider ways in which the elicitation of the numbers (parameters) can be eased.

In Section 6.6 we make some concluding remarks about the art of constructing probabilistic networks by hand, and point out the importance of being aware of the limitations of models and the conditions and assumptions under which they are supposed to work. We also stress that an object-oriented approach, which facilitates a modular model construction approach, should preferably be used for large models or models with repetitive structures (e.g., dynamic models). Finally, we point out that manual model construction is an iterative process that can be quite labor intensive.

## 6.1 When to Use Probabilistic Networks

A probabilistic network is a compact and intuitive representation of causal relations among entities of a problem domain, where these entities are represented as discrete variables over either finite sets of mutually exclusive and exhaustive sets of possible values or as continuous variables defined over a space ranging from minus infinity to plus infinity.

There are many good reasons to choose probabilistic networks as the modeling framework, including the coherent and mathematically sound handling of uncertainty and normative decision making, the automated construction and adaptation of models based on data, the intuitive and compact representation of cause-effect relations and (conditional) dependence and independence relations, the efficient solution of queries given evidence, and the ability to support a whole range of analyses of the results produced, including conflict analysis, sensitivity analysis (with respect to both parameters and evidence), and value-of-information analysis. There are, however, some requirements to

the nature of the problem that have to be fulfilled for probabilistic networks to be the right choice of paradigm for solving the problem.

### 6.1.1 Characteristics of Probabilistic Networks

To understand the power as well as the limitations of the framework of probabilistic networks, let us briefly discuss the main characteristics of probabilistic networks. Probabilistic networks are *normative*, meaning that they provide answers to queries that are mathematically coherent and in agreement with a set of fundamental principles (axioms) of probability calculus and decision theory. There are four ground characteristics that constitute the foundation of (normative) probabilistic models:

- *Graphical representation of causal relations among domain entities (variables).* The notion of causality is central in probabilistic networks, meaning that a directed link from one variable to another (usually) signifies a causal relation among the two. For example, in the Chest Clinic model (see Example 4.2 on page 68), the directed link from **Smoker** to **Bronchitis** indicates that **Smoker** is a (possible) cause of **Bronchitis**.
- *Strengths of probabilistic relations are represented by (conditional) probabilities.* Causal relations among variables are seldomly deterministic in the sense that if the cause is present, then the effect can be concluded by certainty. For example,  $P(\text{Bronchitis} = \text{yes} | \text{Smoker} = \text{yes}) = 0.6$  indicates that among smokers entering the chest clinic 60% suffer from bronchitis.
- *Preferences are represented as utilities on a numerical scale.* All sorts of preferences that are relevant in a decision scenario must be expressed on a numerical scale. In a medical scenario, for example, some relevant factors might be medicine expenses and patient comfort.
- *Recommendations are based on the principle of maximal expected utility.* As the reasoning performed by a probabilistic network is normative, the outcome (e.g., most likely diagnosis or suggested decision) is guaranteed to provide a recommended course of action that maximizes the expected utility to the extent that the model is a “true” representation of problem domain.

### 6.1.2 Some Criteria for Using Probabilistic Networks

Given the characteristics of probabilistic networks, there are obviously some problems that can be modeled nicely with probabilistic networks and others that cannot.

For probabilistic networks to be a good choice of modeling paradigm, there should normally be an element of uncertainty associated with the problem definition, implying a desire to maximize some sort of expected utility.

There are a few problem domains where probabilistic networks might not be the ideal choice of modeling paradigm. For example, some problems concerning pattern recognition (e.g., recognition of fingerprints), where there are

no well-understood mechanisms underlying the layout of the pattern, probabilistic networks most probably would not be the ideal choice. Also, if the cause-effect relations change over time (i.e., there is no fixed structure of the corresponding probabilistic network), other modeling paradigms might be considered.

So, we might set up the following criteria to be met for probabilistic networks to potentially be a good candidate technology for solving the problem at hand:

- *Well-defined variables.* The variables and events (i.e., possible values of the variables) of the problem domain need to be well-defined. For example, in many medical problems the set of relevant factors (e.g., headache, fever, fatigue, abdominal pain, etc.) are well-defined. On the other hand, the variables that determine whether or not a person likes a painting may not be well-defined.
- *Highly structured problem domain with identifiable cause-effect relations.* Well-established and detailed knowledge should be available concerning structure (variables and (causal) links), conditional probabilities, and utilities (preferences). In general, the structure needs to be static (i.e., not changing over time), although re-estimation of structure (often through the usage of learning tools; see Chapter 8) can be performed. The values of the probability parameters of a probabilistic network might be drifting, in which case, adaptation techniques can be used to update the parameter values (see Chapter 8).
- *Uncertainty associated with the cause-effect relations.* If all cause-effect relations are deterministic (i.e., all conditional probabilities either take the value 0 or the value 1), more efficient technologies probably exist. In almost all real-world problem domains there are, however, various kinds of uncertainty associated with cause-effect mechanisms, be it incomplete knowledge about the mechanisms, noisy observations (measurement error), or abstraction of information (e.g., discretization of real-valued observations).
- *Repetitive problem solving.* Often, for the (sometimes large) effort invested in constructing a probabilistic network to pay off, the problem solved should be of repetitive nature. A physician diagnosing respiratory diseases, an Internet company profiling its customers, and a bank deciding to grant loans to its customers are all examples of problems that need to be solved over and over again, where the involved variables and causal mechanisms are invariant over time, and only the values observed for (some of) the variables differ. Although the repetitiveness criterion is characteristic of many real-world decision problems for which model-based decision support is well-suited in terms of payoff of investment, there are important exceptions. Non-repetitive decision problems with high stakes comprise an important exception to this criterion. Examples include decisions on

whether or not to establish an offshore oil rig, build a highway bridge, launch a Mars exploration mission, go to war, etc.

- *Maximization of expected utility.* For the probabilistic network framework to be a natural choice, the problem at hand should most probably contain an element of decision making involving a desire to maximize the expected utility of a decision.

## 6.2 Identifying the Variables of a Model

The set of variables of a probabilistic network comprises the cornerstone of the model. Basically, there are two kinds of variables in probabilistic networks, namely *chance* and *decision* variables. Chance variables model events of the problem domain, which are not under control of the decision maker, whereas decision variables represent precisely the decisions taken by the decision maker.

Variables can be *discrete* or *continuous*. Discrete variables take values from a finite set of possible values, whereas continuous variables take values from the set of real numbers. We refer the reader to Section 4.1.2 for details regarding networks with continuous variables.

### 6.2.1 Well-Defined Variables

A discrete chance variable of a probabilistic network must represent an exhaustive set of mutually exclusive events. That is, all possible values of the variable must be represented in its state space (exhaustiveness) and no pair of values from the set must exclude each other (mutual exclusiveness).

*Example 6.1.* Consider the following sets of events

- (1) {heads, tails},
- (2) {1, 2, 3}, and
- (3) {black\_or\_white, black, white}.

Assume that set (1) is meant to describe the set of possible outcomes of a flip with a coin. Thus, assuming that the coin cannot end up in an upright position, the set constitutes an exhaustive set of mutually exclusive events describing the outcomes, and is thus a positive example of a set of possible states of a variable of a probabilistic network.

Assume that set (2) is meant to describe the outcomes of a roll with an ordinary die. The events of the set are mutually exclusive, but being non-exhaustive, set (2) is a negative example of a set of possible states of a variable of a probabilistic network.

Assume that set (3) is meant to describe the colors of the keys of a piano. The set of events is exhaustive, but not mutually exclusive, and is thus another negative example of a set of possible states of a variable of a probabilistic network.

In addition to representing an exhaustive set of mutually exclusive events, a variable of a probabilistic network typically must represent a *unique* set of events. This means that, usually, a state of a variable should not be mutually exclusive with a state of a single other variable. In other words, the state of a variable should not be given deterministically by the state of a single other variable. If there are states of two variables, say A and B, that are mutually exclusive, it most probably means that the two variables should be merged into one variable having {A, B} as part of its set of states. We shall refer to a test of a variable for fulfillment of this uniqueness property as the *uniqueness test*.

Although we usually require variables to pass the uniqueness test, we do allow (the state of) a variable to be deterministically given by the states of two (or more) other variables. Consider, for example, the Chest Clinic example (see Example 4.2), where `Tub_or_cancer` depends deterministically on variables `Tuberculosis` and `Cancer` through a logical OR relation. Constraint variables (see Chapter 7) also depend deterministically on its parent variables. Such “artificial” variables can be handy in many modeling situations, for example, reducing the number of conditional probabilities needed to be specified or enforcing constraints on the combinations of states among a subset of the variables.

*Example 6.2.* Consider the following candidate variables for a probabilistic network:

- (1) `High_temperature`,
- (2) `Low_temperature`,
- (3) `Error_occured`, and
- (4) `No_error`,

all having state space {no, yes}. Assume that the variables pairwise refer to the state of the same phenomenon (e.g., temperature of cooling water of a power plant and state of operation of a particular device of the plant, respectively). Then there are obviously states of variables `High_temperature` and `Low_temperature` that are mutually exclusive (i.e., `High_temperature` = no implies that `Low_temperature` = yes and vice versa). Obviously, the same problem pertains to variables `Error_occured` and `No_error`.

New variables, say `Temperature` and `Error`, with sets of states {High, Low} and {Error\_occured, No\_error}, respectively, should be defined, and the variables (1)–(4) should be eliminated.

Finally, a candidate variable of a problem domain needs to be clearly defined so that everyone involved in the construction or application of the model (i.e., knowledge engineers, domain experts, decision makers, etc.) knows the exact semantics of each variable of the model. For example, the variable `It_will_rain_tomorrow` might not be clearly defined, as there could be open questions regarding the location of the rain, the amount of rain, the time of observation of rain, etc.



To test if a candidate variable, say  $V$ , is indeed a proper and useful variable of the problem domain, it should be able to pass the *clarity test*:

- (1) The state space of  $V$  must consist of an exhaustive set of mutually exclusive values that  $V$  can take.
- (2) Usually,  $V$  should represent a unique set of events (i.e., there should be no other candidate variable of the problem domain a state of which is mutually exclusive with a state of  $V$ ). If this principle is violated, the model most probably should include one or more “constraint” variables (see Section 7.1.4) to enforce mutual exclusivity.
- (3)  $V$  should be clearly defined, leaving no doubts about its semantics. In general, a variable is well-defined if a clairvoyant can answer questions about the variable without asking further clarifying questions.

Identifying the variables of a problem domain is not always an easy task, and requires some practicing. Defining variables corresponding to the (physical) objects of a problem domain is a common mistake made by most novices. Instead of focusing on objects of the problem domain, one needs to focus on the problem (possible diagnoses, classifications, predictions, decisions, etc. to be made) and the relevant pieces of information for solving the problem.

*Example 6.3 (Doors).* Consider the task of constructing a probabilistic network for the following decision problem (cf. Exercise 5.1 on page 137):

You are confronted with three doors, A, B, and C. Behind exactly one of the doors there is a big prize. The prize is yours if you choose the correct door. After you have made your first choice of door but still not opened it, an official opens another one with nothing behind it, and you are allowed to alter your choice. Now, the question is: Should you alter your choice?

A small probabilistic network can be constructed for solving the problem, and which provides exact odds of winning given the two options. By experience, though, most novices construct models with one variable for each door, instead of variables modeling the information available and the problem to be solved.

By defining a variable for each door (with each variable having state space {Prize, No\_prize}, say), one violates the principle that variables should represent unique sets of events (unless constraint variables are included), and thus do not pass the clarity test.

Instead one needs to take a different perspective, focusing on the problem and the available information:

- (1) *Problem:* Where is the prize? This gives rise to a variable, `Prize_location`, with state space {A,B,C}, corresponding to doors A, B, and C, respectively.
- (2) *Information 1:* Which door did you choose originally? This gives rise to a variable, say `First_choice`, with state space {A,B,C}.

- (3) *Information 2*: Which door were opened by the host? This gives rise to a variable, say `Host_choice`, with state space  $\{A, B, C\}$ .

These variables pass the clarity test.

### 6.2.2 Types of Variables

In the process of identifying the variables it can be useful to distinguish between different types of variables:

- *Problem variables*: These are the variables of interest; i.e., those for which we want to compute their posterior probability given observations of values for information variables (see next item). Usually, the values of problem variables cannot be observed; otherwise, there would not be any point in constructing a probabilistic network in the first place. Problem variables (also sometimes called *hypothesis variables*) relate to diagnoses, classifications, predictions, decisions, etc. to be made.
- *Information variables*: These are the variables for which observations may be available, and which can provide information relevant for solving the problem. Two sub-categories of information variables can be distinguished:
  - *Background information*: Background information for solving a problem (represented by one or more problem variables) is information that was available before the occurrence of the problem and that has a causal influence on problem variables and symptom variables (see next item), and are thus usually among the “root” variables of a probabilistic network. For example, in a medical setting, relevant background information could include patient age, smoking habits, blood type, gender, etc.
  - *Symptom information*: Symptom information, on the other hand, can be observed as a consequence of the presence of the problem, and hence will be available after the occurrence of the problem. In other words, problem variables have causal influences on its symptoms. Hence, symptom variables are usually descendants of background and problem variables. Again, in a medical setting, relevant symptom information could include various outcomes of clinical tests and patient interviews; e.g., blood pressure, fever, headache, weight, etc.
- *Mediating variables*: These are unobservable variables for which posterior probabilities are not of immediate interest, but which play important roles for achieving correct conditional independence and dependence properties and/or efficient inference. Mediating variables often have problem and background variables as parents and symptom variables as children.

Table 6.1 summarizes the typical causal dependence relations for the four different variable classes.

In Example 6.3 there are one problem variable (`Prize_location`) and two information variables (`First_choice` and `Host_choice`), where `First_choice` represents a piece of background information, as it was available before the problem

Type	Causally influenced by
Background variables	None
Problem variables	Background variables
Mediating variables	Background and problem variables
Symptom variables	Background, problem, and mediating variables

**Table 6.1.** Typical causal dependence relations for different variable classes.

occurred, and `Host_choice` represents a piece of symptom information that became available only after the occurrence of the problem and as a consequence of it.

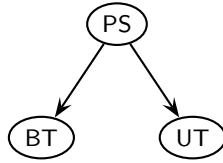
*Example 6.4 (Classification).* Assume that we wish to construct a probabilistic network for classifying scientific papers into the two classes of

- (1) books referring to real-world applications of Bayesian networks and
- (2) other books.

We identify a problem variable, say `Class`, with two states, say `BN_appl.books` and `Other.books`. Assume that the classification is going to be based on detection of keywords, where keywords like “Bayesian network”, “Bayes net”, “application”, “industrial”, “decision support”, etc. found in a book might indicate reference to real-world applications of Bayesian networks. Then we might define an information (symptom) variable for each keyword (or phrase). Each information variable could be binary; e.g., Boolean, with states 0 (“false”) and 1 (“true”) indicating if the keyword is absent or present, respectively, in a particular book). In a more refined version, each information variable could represent the number of occurrences of the associated keyword, in which case the variable need several states, say  $\{0, 1 - 5, 5 - 15, > 15\}$ .

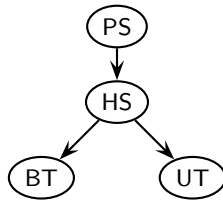
Example 6.5 provide a simple example in which the need for a mediating variable is crucial for achieving correct dependence and independence properties of a model (and, consequently, to get reliable answers from the model).

*Example 6.5 (Insemination (Jensen 2001)).* Six weeks after insemination of a cow, two tests can be performed to investigate the pregnancy state of the cow: blood test and urine test. We identify pregnancy state as the problem variable (PS), and the results of the blood and urine tests as information (symptom) variables (BT and UT, respectively), where PS has states `{Pregnant, Not_pregnant}` and variables (BT and UT have states `{Positive, Negative}`). As the state of pregnancy has a causal influence on the outcome of the tests, we identify an initial model as shown in Figure 6.1. Using d-separation, we find that this model assumes BT and UT to be independent given information about the state of PS (i.e.,  $P(\text{PS} = \text{Pregnant}) = 0$  or  $P(\text{PS} = \text{Pregnant}) = 1$ ). Assume now that a domain expert (e.g., a veterinarian) informs us that this independence statement is false; i.e., the expert



**Fig. 6.1.** A model for determining pregnancy state.

expects the outcome of one of the tests to be informative about the outcome of the other test even if the pregnancy state of the cow is known for sure. As there are no natural causal mechanisms linking BT and UT that could counter for the dependence between these two variables, we need to solve the problem by introducing a fourth (mediating) variable (HS) describing the hormonal state of the cow, which determines the outcomes of both tests (i.e., HS has a causal influence on BT and UT). The resulting model is shown in Figure 6.2, where BT and UT are dependent (as they should be) even if the state of pregnancy is known.



**Fig. 6.2.** A refined model for determining the pregnancy state, reflecting the fact that both tests are indications of the hormonal state, which in turn is an indication of pregnancy state.

## 6.3 Eliciting the Structure

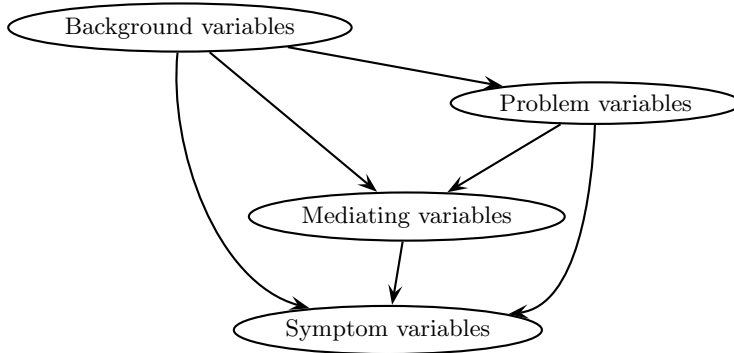
We shall consider two structured ways of eliciting the model structure. A basic approach relies on the natural causal ordering that exist among the four categories of variables that were discussed in Section 6.2.2. A more refined approach has been developed by Neil et al. (2000) where model fragments are identified by recognizing archetypical relations (known as *idioms*) among groups of variables.

### 6.3.1 A Basic Approach

Given an initial set of variables identified for a given problem domain, the next step in the model construction process concerns the identification and

verification of (causal) links of the model. As discussed in Section 2.4, maintaining a causal perspective in the model construction process may prove valuable in terms of correctly representing the dependence and independence relations as well as in terms of ease of elicitation of the conditional probabilities of the model. Notice that maintaining a causal perspective is crucial when constructing influence diagrams (see Chapter 4).

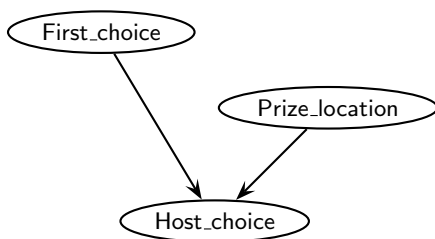
As discussed in Section 6.2.2, there are four categories of variables of a probabilistic network: (i) background (information) variables, (ii) problem variables, (iii) mediating variables, and (iv) symptom (information) variables. Also, as discussed above, background variables have a causal influence on problem variables and symptom variables, and problem variables have a causal influence on symptom variables. Mediating variables, if present, are most often causally influenced by problem variables and background variables, and they causally influence symptom variables. This gives us a typical overall causal structure of a probabilistic network as shown in Figure 6.3.



**Fig. 6.3.** Typical overall causal structure of a probabilistic network.

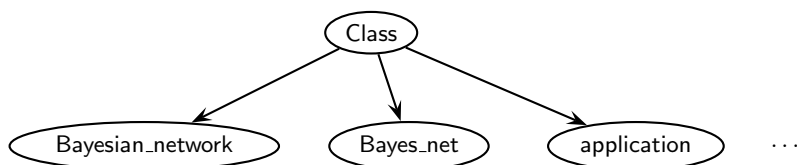
Notice that the structure of the chest-clinic example on page 68 fits nicely with this overall structure of a probabilistic network, where *Asia* and *Smoker* are background variables, *Tuberculosis*, *Cancer*, and *Bronchitis* are problem variables, *Tub\_or\_cancer* is a mediating variable, and *X\_ray* and *Dyspnoea* are symptom variables.

*Example 6.6 (Doors, continued).* For the decision problem of Example 6.3 on page 149 we identified *First\_choice* as a background variable, *Prize\_location* as a problem variable, and *Host\_choice* as a symptom variable. Obviously, *First\_choice* has no influence on *Prize\_location* (i.e., no cheating by the host). Also, clearly, the choice of the host depends on your initial choice (*First\_choice*) as well as on the host's private information about the location of the prize (*Prize\_location*). Thus, following the overall structure in Figure 6.3, we arrive at a structure for the problem as shown in Figure 6.4.



**Fig. 6.4.** Causal structure for the prize problem.

*Example 6.7 (Classification, continued).* In Example 6.4 on page 151 we have one problem variable `Class` and a number of symptom variables, say `Bayesian_network`, `Bayes_net`, `application`, `industrial`, `decision_support`, etc. According to the overall structure in Figure 6.3, we get a network structure as displayed in Figure 6.5.



**Fig. 6.5.** Structure of the model for the classification problem of Example 6.4.

### 6.3.2 Idioms

Neil et al. (2000) have developed an approach to elicitation of model structure, which is based on describing the semantics and syntax of five commonly occurring substructures (called *idioms*), representing different modes of uncertain reasoning. These five idioms are believed to cover the vast majority, if not all, substructures that can occur in a Bayesian network. Each idiom can be considered an archetypical set of relations among a set of variables. Thus, the use of idioms encourages the knowledge engineer to think in terms of semantical relations among a (small) group of variables rather than in terms of nodes and links. The modeling paradigm is thus moved to a higher level of abstraction, leaving details about which links to include and their directionality to be handled automatically through the predefined structures of the idioms.

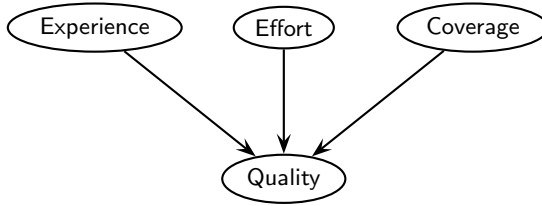
The five idioms are:

- (1) *Definitional/synthesis*: Models the combination of variables into a single variable, including deterministic or uncertain definition/function of a variable in terms of other variables.

- (2) *Cause–consequence*: Models cause–effect mechanisms (causal processes).
- (3) *Measurement*: Models the uncertainty associated with an observation or measurement.
- (4) *Induction*: Models inductive reasoning based on observations from similar entities to infer something about an unobserved entity.
- (5) *Reconciliation*: Models the reconciliation of results from competing statements that arise from different sources of information.

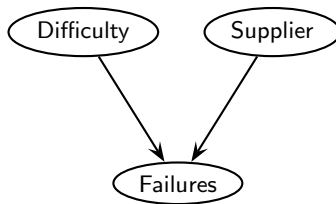
Let us consider some examples on the use of the idioms, all taken from the problem domain of risk assessment in software development processes (Neil et al. 2000).

*Example 6.8 (Definitional/synthesis idiom (Neil et al. 2000))*. The quality of software testing is defined in terms of the experience of the tester, the effort put into the testing process, and the coverage of the test (i.e., how many modules of the software system is tested). A sub-model implementing this definition of testing quality as an instance of the definitional/synthesis idiom is shown in Figure 6.6.



**Fig. 6.6.** Sample instantiation of the definitional/synthesis idiom (Neil et al. 2000).

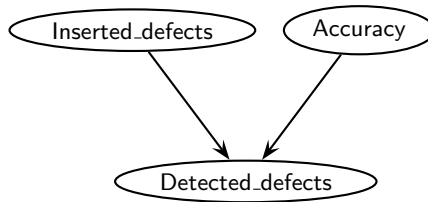
*Example 6.9 (Cause–consequence idiom (Neil et al. 2000))*. Both problem difficulty and supplier quality have causal impacts on the number of failures in a software product. The three variables, *Difficulty*, *Supplier*, and *Failures*, comprise a sub-model implemented as a join of two instantiations of the cause–consequence idiom, as illustrated in Figure 6.7.



**Fig. 6.7.** Sample instantiation of the cause–consequence idiom (Neil et al. 2000).

One might argue that in Example 6.8 *Experience*, *Effort*, and *Coverage* are all causes of *Quality*, and hence these four variables comprise a sub-model implemented as a join of three instantiations of the cause–consequence idiom. Also, in Example 6.9, one might argue that variable *Failures* is defined in terms of (or is a synthesis of) variables *Difficulty* and *Supplier*, and hence should give rise to a sub-model implemented as an instance of the definitional/synthesis idiom. Which of the two idioms is chosen, however, is immaterial and depends on how the model constructor perceives the relations among the variables.

*Example 6.10 (Measurement Idiom (Neil et al. 2000)).* The number of defects in a software system can only be estimated up to a certain accuracy. Still, however, the true number of defects is the important variable in assessing the risk of employing the system. Hence, based on the observed number of defects (*Detected\_defects*), we need to estimate the true number (*Inserted\_defects*). In doing that we need to know the accuracy of the testing procedure applied. This is a classical example of an instantiation of the measurement idiom, as illustrated in Figure 6.8.

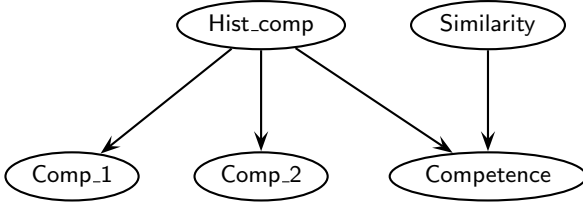


**Fig. 6.8.** Sample instantiation of the measurement idiom (Neil et al. 2000).

*Example 6.11 (Induction Idiom (Neil et al. 2000)).* Assume that information is available on the competence of a software testing organization on two previous occasions, where the organization tested non-critical software products. Given this information and a measure on the similarity of these previous software products with a safety-critical software product, we wish to estimate the competence of the organization in testing the safety-critical product. In other words, we wish to induce the competence from previous competences on similar tasks. This induction problem is implemented as an instantiation of the induction idiom, as illustrated in Figure 6.9.

*Example 6.12 (Reconciliation Idiom (Neil et al. 2000)).* Statements about fault tolerance of a software system can be derived either through a cause–consequence relation, where the quality of the software development process has a causal influence on the fault tolerance of the system, or through a definitional relation involving the contributions of various fault tolerance strategies such as error checking and error recovery mechanisms. Thus, if two such competing submodels provide statements about fault tolerance, we need to reconcile the two statements. Figure 6.10 shows how this problem can be solved



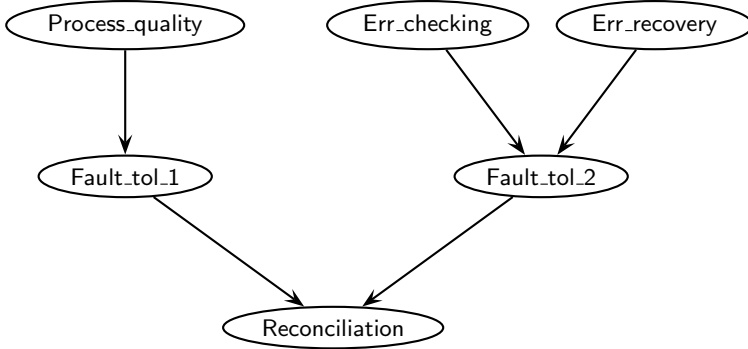


**Fig. 6.9.** Sample instantiation of the induction idiom (Neil et al. 2000).

through an instantiation of the reconciliation idiom, where *Reconciliation* is a binary variable with states *on* and *off* that forces  $P(\text{Fault\_tol\_1}|\varepsilon)$  and  $P(\text{Fault\_tol\_2}|\varepsilon)$  to be identical whenever *Reconciliation* = *on*, i.e.,

$$P(R = \text{on} | F_1, F_2) = \begin{cases} 1 & \text{whenever } F_1 = F_2 \\ 0 & \text{otherwise,} \end{cases}$$

where  $F_1$ ,  $F_2$ , and  $R$  are abbreviations for, respectively, *Fault\_tol\_1*, *Fault\_tol\_2*, and *Reconciliation*. Assume that  $\text{dom}(F_1) = \text{dom}(F_2) = \{\text{high}, \text{low}\}$  and that



**Fig. 6.10.** Sample instantiation of the reconciliation idiom (Neil et al. 2000).

before reconciliation has taken place (i.e.,  $R$  has not been instantiated) we have

$$P(F_1 = \text{high} | \varepsilon) = 0.7$$

$$P(F_2 = \text{high} | \varepsilon) = 0.8.$$

Using Bayes' rule (Equation 3.11), we then get

$$\begin{aligned}
& P(F_1 = \text{high} | R = \text{on}, \varepsilon) \\
&= \frac{P(F_1 = \text{high}, R = \text{on} | \varepsilon)}{P(R = \text{on} | \varepsilon)} \\
&= \frac{P(R = \text{on} | F_1 = \text{high}, F_2 = \text{high})P(F_1 = \text{high} | \varepsilon)P(F_2 = \text{high} | \varepsilon)}{P(R = \text{on} | \varepsilon)} \\
&\quad + \frac{P(R = \text{on} | F_1 = \text{high}, F_2 = \text{low})P(F_1 = \text{high} | \varepsilon)P(F_2 = \text{low} | \varepsilon)}{P(R = \text{on} | \varepsilon)} \\
&= \frac{1 \cdot P(F_1 = \text{high} | \varepsilon)P(F_2 = \text{high} | \varepsilon) + 0 \cdot P(F_1 = \text{high} | \varepsilon)P(F_2 = \text{low} | \varepsilon)}{\sum_{F_1, F_2} P(R = \text{on} | F_1, F_2)P(F_1 | \varepsilon)P(F_2 | \varepsilon)} \\
&= \frac{P(F_1 = \text{high} | \varepsilon)P(F_2 = \text{high} | \varepsilon)}{P(F_1 = \text{high} | \varepsilon)P(F_2 = \text{high} | \varepsilon) + P(F_1 = \text{low} | \varepsilon)P(F_2 = \text{low} | \varepsilon)}.
\end{aligned}$$

(Note that with the last expression being symmetrical in  $F_1$  and  $F_2$ , we get (as expected)  $P(F_1 = \text{high} | R = \text{on}, \varepsilon) = P(F_2 = \text{high} | R = \text{on}, \varepsilon)$ .) Now, with  $P(F_1 = \text{high} | \varepsilon) = 0.7$  and  $P(F_2 = \text{high} | \varepsilon) = 0.8$ , we get

$$P(F_1 = \text{high} | R = \text{on}, \varepsilon) = P(F_2 = \text{high} | R = \text{on}, \varepsilon) = 0.903.$$

That is, the reconciliation model reinforces both statements whenever the statements support each other; i.e., if  $P(F_1 = \text{high} | \varepsilon) > \frac{1}{2}$  and  $P(F_2 = \text{high} | \varepsilon) > \frac{1}{2}$ , then

$$P(F_i = \text{high} | R = \text{on}, \varepsilon) > \max\{P(F_1 = \text{high} | \varepsilon), P(F_2 = \text{high} | \varepsilon)\}$$

for  $i = 1, 2$ . Similarly, with the above sample values for  $P(F_1 = \text{high} | \varepsilon)$  and  $P(F_2 = \text{high} | \varepsilon)$ ,

$$P(F_i = \text{low} | R = \text{on}, \varepsilon) < \min\{P(F_1 = \text{low} | \varepsilon), P(F_2 = \text{low} | \varepsilon)\}$$

for  $i = 1, 2$ .

Some remarks concerning the feasibility of the reconciliation idiom are in order. As shown in Example 6.12 on page 156, the model reinforces statements supporting each other. That is, the posterior probability (i.e., after reconciliation) of a statement is greater (less) than the prior probability of the statement if the prior probability of each of the contributing statements is greater (less) than  $\frac{1}{2}$ . In applications like the one sketched in Example 6.12, this might make perfect sense, as two different sources of information form the bases of the two statements about fault tolerance; i.e., one is based on an assessment of process quality, and another on the extent to which errors have been checked for and the ability of the system to recover from errors. Thus, whenever two such independent statements about the fault tolerance of a system both point in the same direction there is reason to believe that the combined statement is stronger than each individual statement.

Care should be taken, however, not to apply the reconciliation model in cases where the contributing/competing statements are based on the same

source of information. Consider, for example, the statements from two, otherwise independent, astronomers about the risk of an asteroid hitting the Earth. If each of them state that the risk of collision is 10%, it would definitely be a mistake to conclude that the risk then would be only 1.2%, which would be the result of applying the reconciliation model in this case! In Section 7.2.2 we shall present a model for dealing with competing statements that are based on the same source of information.

The basic structures of the idioms are illustrated in Figure 6.11. Notice that these basic structures can be combined into more complex structures. For example, parents in a definitional/synthesis idiom can be a child in another definitional/synthesis idiom etc., breaking down a definitional/synthesis idiom with many parents into a hierarchy through a parent divorcing process (see Chapter 7). Also, basic cause–consequence idioms are typically combined into more complex structures where causes have common effects and effects have common causes.

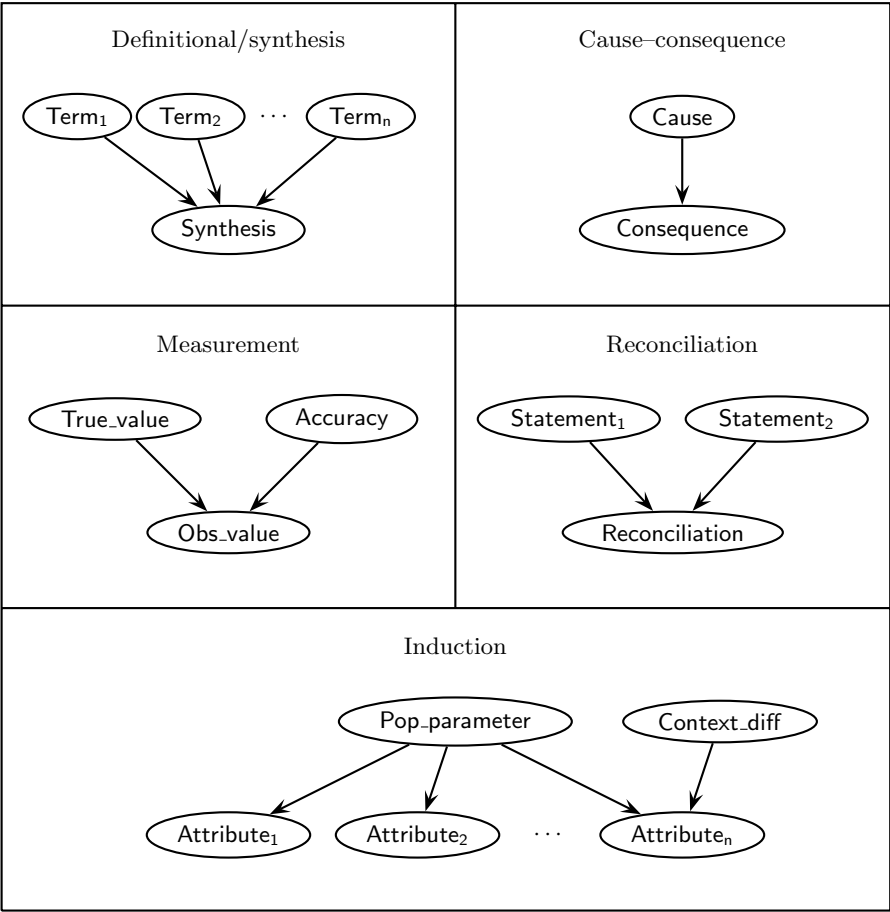
Also notice that depending on whether or not a root variable of an idiom is a root variable of the overall model structure it may be categorized as either a background variable, a problem variable, or a mediating variable. Similarly, a non-root variable of an idiom may be a problem variable, a mediating variable, or a symptom variable of the overall model. For example, in the induction idiom of Figure 6.9 on page 157, variables `Hist_comp` and `Similarity` could typically be characterized as background variables, `Comp_1` and `Comp_2` as symptom variables, and `Competence` as a problem variable.

Probably the most frequent idiom used is the cause–consequence idiom. Thus, in determining the “right” idiom to use it might be advisable to start considering whether the relations among the subset of variables under consideration are best described using one or more cause–consequence relations. Also, the measurement, induction and reconciliation idioms all deal with assessments of some sort. Therefore, another relevant question to ask is whether the relations among the variables under consideration describe some sort of assessment. As a guide to choosing the right idiom one might consult the flowchart in Figure 6.12.

## 6.4 Model Verification

Proper use of idioms or identification and categorization of variables as background variables, problem variables, symptom variables, and mediating variables and adhering to the overall causal structure in Figure 6.3 reduces the typical error of letting links (arrows) point from symptom variables to problem variables. If, however, a model contains links that point from effects to causes, inspection of the dependence and independence properties represented by the model will often reveal a problem caused by the reversed links.

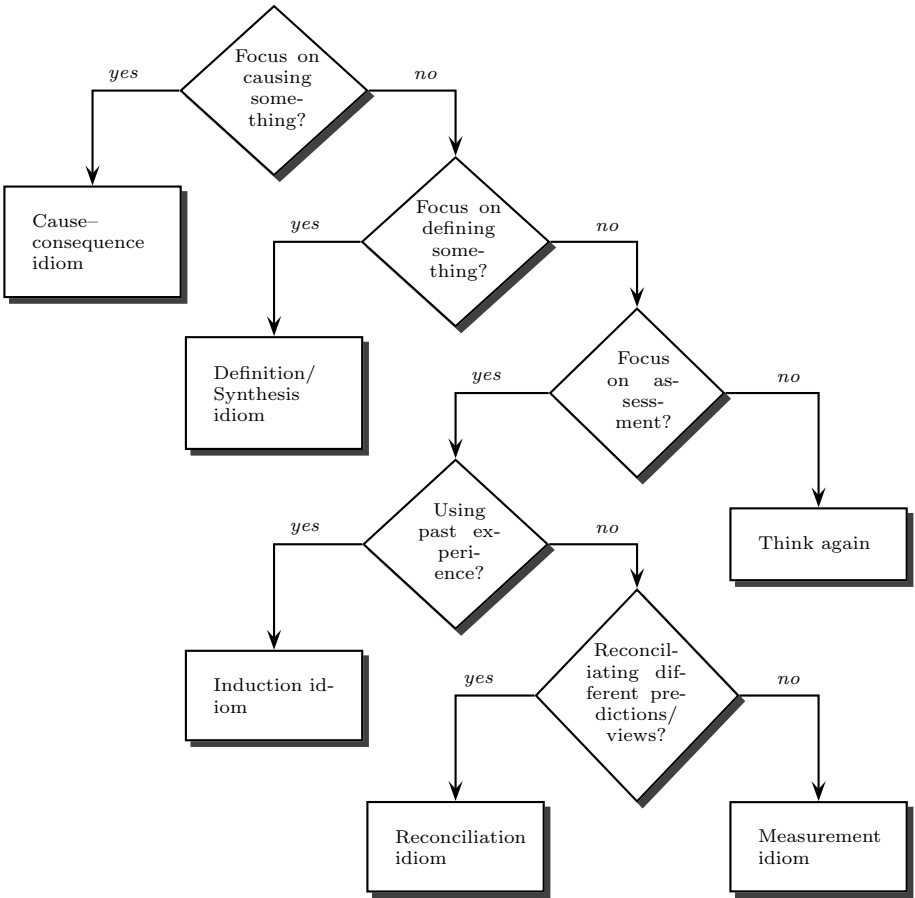
*Example 6.13.* Consider the following three Boolean variables (i.e., having state space {false, true}):



**Fig. 6.11.** The five basic kinds of idioms defined by Neil et al. (2000).

- **Two\_PCs:** Two or more PCs have been bought within a few days using the same credit card.
- **Card\_copied:** The credit card has been used at almost the same time at different locations.
- **Fraud:** The credit card has been subject to fraud.

Now the question is if Model A in Figure 6.13(a) is correct or Model B in Figure 6.13(b) is correct. Experience shows that most novices tend to prefer Model A, probably based on the notion that “input” leads to “output” (i.e., observations imply a hypothesis). That is, given the two pieces of information that the credit card has been used to buy two or more PCs within a few days and that the card has been used almost at the same time at different



**Fig. 6.12.** Choosing the right idiom (Neil et al. 2000).



**Fig. 6.13.** Two competing models for Example 6.13.

locations (the input), we can conclude that the card has been subject to fraud (the output). According to Model A, however, information about `Two_PCs` (`Card_copied`) does not provide us with any information about `Card_copied` (`Two_PCs`) when no information is available about `Fraud`. This is obviously incorrect, as one piece of evidence confirming (or disconfirming) fraud would obviously make us believe more (or less) in observing the other symptom of fraud. Based on Model A we would thus get wrong posterior probabilities. Notice also that Model A does not have the typical causal structure as displayed in Figure 6.3, as we identify `Fraud` as the problem variable and `Two_PCs` and `Card_copied` as information (symptom) variables.

Model B, on the other hand, rightfully tells us that

- `Two_PCs` and `Card_copied` are dependent when we have no hard evidence on `Fraud`: Observing `Two_PCs` (`Card_copied`) will increase our belief that we will also observe `Card_copied` (`Two_PCs`), and
- `Two_PCs` and `Card_copied` are independent when the state of `Fraud` is known: If we know that we are considering a case of fraud, then observing `Two_PCs` (`Card_copied`) will not change our belief about whether or not we are going to observe `Card_copied` (`Two_PCs`).

As this example shows, close inspection of the dependence and independence relations of a model may reveal links pointing in the wrong direction. However, adherence to the overall causal structure of Figure 6.3, would eliminate the possibility of arriving at Model A.

Using the idiom approach to structure elicitation in this case, one would have to decide whether to use the definitional/synthesis idiom or the cause–consequence idiom (the measurement, reconciliation, and induction idioms would be readily rejected). The definitional/synthesis idiom would make `Fraud` be defined in terms of `Card_copied` and `Two_PCs`, which would be awkward. For one thing, such a definition would be open-ended, as there are an unlimited number of ways in which a credit card can be abused. Another, more convincing, argument why the definitional/synthesis idiom is the wrong choice is that it violates the overall causal structure of Figure 6.3.

Despite its simplicity, Example 6.13 shows that it might be beneficial to combine the idiom approach and the basic approach to structure elicitation. In other words, keeping in mind the overall causal structure of Figure 6.3 might be helpful when a choice of idiom has to be made.

As illustrated in Example 6.5 on page 151, model verification may reveal a need to introduce additional (mediating) variables. The mediating variable, `HS`, of Figure 6.2 is a common cause of variables `BT` and `UT`. Identification of such common causes most often requires a close collaboration between a problem domain expert and a knowledge engineer, as the domain expert often lacks the ability to read the dependence and independence properties displayed by a network structure and the knowledge engineer lacks insight into the causal mechanisms among the variables of problem domain. As illustrated

in the pregnancy example, failure to identify such hidden common causes (i.e., causes for which we have neither any immediate interest in their probability distributions nor any (easy) way of observing their states) may lead to models that provide wrong answers. In the case of the pregnancy model, exclusion of the variable HS would make the model exaggerate the influence from BT and UT when both are observed, as they are both indicative of the same phenomenon, namely a possible change in the hormonal state of the cow.

## 6.5 Eliciting the Numbers

Once the structure of the probabilistic network has been established — probably through an iterative process involving model verification and model revisions, including identification of new variables, deletion and redefinition of existing variables, and addition, deletion, and reversal of links — the next and usually the most difficult phase of constructing a probabilistic network concerns the elicitation of the quantitative information, including (conditional) probability distributions and utilities (jointly referred to as the “numbers” or the “parameters”).

Due to the (most often) quite demanding effort involved in eliciting the numbers, it is important to carefully verify the structure of the model before proceeding to the quantitative part of the model construction. Otherwise, one runs the risk of having to reject or alter already elicited numbers, as the kind of numbers required are dictated by the model structure. Also, eliciting conditional probabilities with causal links reversed may be difficult and prone to errors. In practice, however, minor model structure adjustments are often made during the number elicitation process (e.g., to reduce the number of parameters).

The quantitative information of a probabilistic network (often referred to as the parameters of the model) is represented as real numbers in conditional probability tables (CPTs) and utility tables (UTs). CPTs represent (conditional) probability distributions with domains spanning the interval  $[0; 1]$ , whereas UTs represent utility functions with domains spanning  $]-\infty; \infty[$ .

The parameters of a probabilistic network can be retrieved from databases, elicited from (subjective) domain expert knowledge (e.g., from literature or interviews of domain experts), or established through a mathematical model (e.g., based on assumptions that a given probabilistic distribution can be approximated through a mixture of two Normal distributions). In this section, we shall focus only on the latter two approaches; see Chapter 8 for learning probability parameters from data.

### 6.5.1 Eliciting Subjective Conditional Probabilities

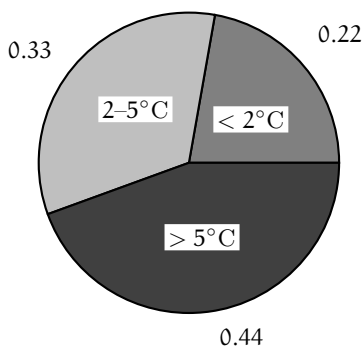
Part of the reason why elicitation of values of probability parameters can be rather demanding is that human reasoning is seldomly based on probabilities.

In other words, a domain expert might find it awkward to express her domain-specific knowledge in terms of conditional probabilities and utility values. Thus, different indirect ways of eliciting the quantitative knowledge may be used.

The fact that small differences in the values of probability (or utility) parameters often make no difference in the recommendations provided by a model allows for parameter elicitation methods based on qualitative approaches. A qualitative approach often makes the domain expert more comfortable specifying her knowledge about strengths of causal relations and relative preferences associated with decision problems.

An example of a qualitative approach for assessing subjective probabilities include the usage of a so-called *probability wheel*. A probability wheel is a circle subdivided into  $n$  pie wedges, where  $n$  equals the number of possible states of the variable for which a (conditional) probability distribution is requested. The domain expert then estimates a probability for a particular state by sizing the corresponding pie wedge to match her best assessment of that probability.

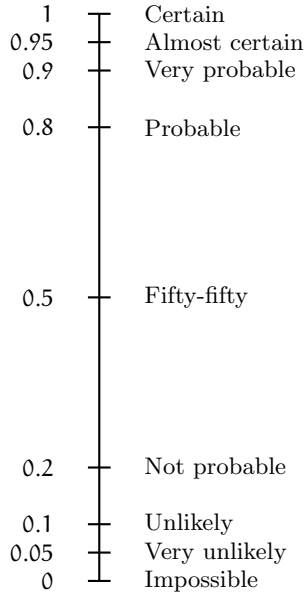
*Example 6.14 (Probability Wheel).* A climate researcher asked to provide an estimate of the increase in the average global temperature over the next 100 years might use a probability wheel as shown in Figure 6.14, working with a granularity of  $< 2^\circ\text{C}$ ,  $2\text{--}5^\circ\text{C}$ , and  $> 5^\circ\text{C}$ .



**Fig. 6.14.** Probability wheel with three pie wedges corresponding to three states of a variable representing the increase in the average global temperature over the next 100 years. The relative area occupied by a particular pie wedge represents the (conditional) probability for the associated state (indicated by the numbers next to the pie wedges).

Another example of a qualitative approach is the use of verbal statements like “very unlikely” or “almost certain” that are then mapped to probabilities (see Figure 6.15). The use of such a limited set of verbal statements often makes it quite a lot easier for the domain expert to provide assessments of (conditional) probabilities.





**Fig. 6.15.** Mapping of verbal statements of probability to probabilities.

A simple gamble-based approach can be used for assessing the value of a probability parameter. Assume that a domain expert is asked to assess the conditional probability that  $X = x$  when  $Y = y$ ; i.e.,  $P(X = x|Y = y)$ . An indirect way of making the expert assess this quantity would be to ask the expert to choose an  $n$ , where  $0 \leq n \leq 100$ , such that she finds the following two gambles equally attractive:

- (1) If  $X$  attains the value  $x$  when  $Y = y$ , you receive \$10.
- (2) If you draw a red ball from an urn with  $n$  red balls and  $100 - n$  white balls, you receive \$10.

If all balls are red, she prefers Gamble 2, and if all balls are white, she prefers Gamble 1. The  $n$  for which she finds the two gambles equally attractive is her estimate of  $100 * P(X = x|Y = y)$ ; i.e.,  $P(X = x|Y = y) = n/100$ .

To reduce the parameter elicitation burden, it is advisable to perform the elicitation of probability parameters in a two-step process:

- (1) quickly provide rough initial parameter estimates, and then
- (2) perform sensitivity analysis (see Chapter 10) to identify parameter assessments that need to be made with care, as small variations can have a large impact on the posterior probability of problem variables given evidence.

The second step should probably be repeated, as the careful assessment of the critical parameters might reveal new critical parameters, etc.

See, for example, Renooij (2001) for a more in-depth discussion of the issues related to elicitation of probabilities for probabilistic networks.

### 6.5.2 Eliciting Subjective Utilities

Similar to the gamble-based approach for eliciting subjective conditional probabilities, we define a gamble-based approach for eliciting subjective utilities.

Assume that we have the ordering  $(a_1, \dots, a_n)$  of outcomes to which we need to assign subjective utilities, where the outcomes are ordered from worst to best. We first assign a utility of 0 to the worst outcome and a utility of 1 to the best outcome. So

$$U(a_1) = 0$$

$$U(a_n) = 1.$$

Then we consider gambles (or lotteries)  $L_p$  in which we get the best outcome  $(a_n)$  with probability  $p$  and the worst outcome  $(a_1)$  with probability  $1 - p$ . The utility of an outcome  $a_i$  ( $i = 2, \dots, n - 1$ ) is then defined to be the expected utility of  $L_p$  for which we are indifferent between playing the gamble and getting the outcome  $a_i$  for sure. Thus,

$$\begin{aligned} U(a_i) &= EU(L_p) \\ &= p \cdot U(a_n) + (1 - p) \cdot U(a_1) \\ &= p. \end{aligned}$$

In other words, the probability,  $p$ , for which we are indifferent between the gamble and getting  $a_i$  for sure is our utility for  $a_i$ .

### 6.5.3 Specifying CPTs and UTs Through Expressions

Probability distributions and utility functions in probabilistic networks often follow (at least approximately) certain functional or distributional forms. In such cases the CPTs/UTs can be described compactly through mathematical expressions. Apart from ease of specification, specification through expressions also makes maintenance and reuse much easier.

An expression may be built using standard statistical distributions (e.g., Normal, Binomial, Beta, Gamma, etc.), arithmetic operators, standard mathematical functions (e.g., logarithmic, exponential, trigonometric, and hyperbolic functions), logical operators (e.g., and, or, if-then-else), and relations (e.g., less than, equals).

The different operators used in an expression have different return types and different type requirements for arguments. Thus, in order to provide a rich language for specifying expressions, it is convenient to have a classification of the discrete chance and decision variables into different groups:

- *Labeled variables* have state spaces of arbitrary qualitative descriptors provided in the form of character strings. Labeled variables can be used in equality comparisons and to express deterministic relationships. For example, a labeled variable  $C_1$  with states `state_1` and `state_2` can appear in

an expression like `if(C1 = state_1, Distribution(0.2, 0.8), Distribution(0.4, 0.6))` for  $P(C_2 | C_1)$ , where  $C_2$  is another discrete chance variable with two possible states and where `if(p, a, b)` is read as if predicate  $p$  is true, then  $a$  else  $b$ .

- *Boolean variables* represent the truth values “false” and “true” (in that order) and can be used in logical operators. For example, for a Boolean variable,  $B_0$ , being the logical OR of its (Boolean) parents,  $B_1$ ,  $B_2$ , and  $B_3$ ,  $P(B_0 | B_1, B_2, B_3)$  can be specified simply as `or(B1, B2, B3)`.
- *Numbered variables* represent increasing sequences of numbers (integers or reals) and can be used in arithmetic operators, mathematical functions, etc. For example, a numbered variable with state space  $\{1, 2, 3, 4, 5, 6\}$  can represent the outcome of the roll of a die.
- *Interval variables* represent disjoint intervals on the real line and can be used in the same way as numbered variables. In addition, they can be used when specifying the intervals over which a continuous quantity is to be discretized. For example, an interval variable with state space  $\{[0; 2], [2; 5], [5; 10]\}$  may represent the increase in the average global temperature over the next 100 years (cf. Example 6.14 on page 164).

Table 6.2 shows some examples of possible states of the various subtypes of discrete chance variables.

Subtype	Sample states
Labeled	red, blue, low
Boolean	false, true
Numbered	$-\infty, \dots, -2.2, -1.5, 0, 1, 2, 3, \dots, \infty$
Interval	$] - \infty; -10], ] - 10; -5], ] - 5; -1]$

**Table 6.2.** Examples of possible states of the various subtypes of discrete chance variables.

Based on the semantics of discrete chance nodes provided by the above subtyping an algorithm for automatic generation of CPTs and UTs can be implemented. The functionality of such a table generator will be dependent on the subtypes of the variables involved. Table 6.3 shows how the functionality of a table generator algorithm might be dependent on variable subtypes.

*Example 6.15 (Number of People (Hugin 2006)).* Assume that in some application we have probability distributions over the number of males and females, where the distributions are defined over intervals  $]0; 100]$ ,  $]100; 500]$ ,  $]500; 1000]$ , and that we wish to compute the distribution over the total number of individuals given the two former distributions. (Note that this an obvious sample usage of the definitional/synthesis idiom presented in Section 6.3.2 on page 155.) It is a simple but tedious task to specify  $P(N_I | N_M, N_F)$ , where  $N_I$ ,  $N_M$ , and  $N_F$  stand for the number of individuals, the number of males, and the number

Operation	Labeled	Boolean	Numbered	Interval	Utility
if-then-else	+	+	+	+	+
Arithmetic operators			+	+	+
Boolean operators		+			
Boolean comparison		+			
Boolean distributions		+			
Continuous distributions				+	
Discrete distributions			+		
Custom distribution	+				

**Table 6.3.** The functionality of a table generator algorithm is dependent on the subtype of the involved variables.

of females, respectively. A much more expedient way of specifying this conditional probability distribution would be to let  $N_M$  and  $N_F$  be interpreted as interval variables with states  $]0; 100]$ ,  $]100; 500]$ , and  $]500; 1000]$ , and to let  $N_I$  be interpreted as an interval variable with states  $]0; 200]$ ,  $]200; 1000]$ , and  $]1000; 2000]$ , for example, and then define  $P(N_I|N_M, N_F)$  through the simple expression  $N_I = N_M + N_F$ . The alternative would require specification (including computation) of 27 probability parameters; see Table 6.4.

$N_F$	$N_M$	$N_I$		
		$]0; 200]$	$]200; 1000]$	$]1000; 2000]$
$]0; 100]$	$]0; 100]$	1	0	0
$]0; 100]$	$]100; 500]$	0.1248	0.8752	0
$]0; 100]$	$]500; 1000]$	0	0.8960	0.1040
$]100; 500]$	$]0; 100]$	0.1248	0.8752	0
$]100; 500]$	$]100; 500]$	0	1	0
$]100; 500]$	$]500; 1000]$	0	0.4	0.6
$]500; 1000]$	$]0; 100]$	0	0.8960	0.1040
$]500; 1000]$	$]100; 500]$	0	0.4	0.6
$]500; 1000]$	$]500; 1000]$	0	0	1

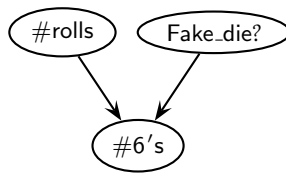
**Table 6.4.** The CPT for  $P(N_I|N_M, N_F)$  in Example 6.15 generated from the expression  $N_I = N_M + N_F$ .

*Example 6.16 (Fair or Fake Die (Hugin 2006)).* Consider the problem of computing the probabilities of getting  $n$  sixes in  $n$  rolls with a fair die and a fake die, respectively. A random variable,  $X$ , denoting the number of sixes obtained in  $n$  rolls with a fair die is binomially distributed with parameters  $(n, 1/6)$ . Thus, the probability of getting  $k$  sixes in  $n$  rolls with a fair die is  $P_{\text{fair}}(X = k)$ , where  $P_{\text{fair}}$  is a **Binomial** $(n, 1/6)$ . Assuming that for a fake die the probability of six pips facing up is  $1/5$ , the probability of getting  $k$  sixes in  $n$  rolls with a fake die is  $P_{\text{fake}}(X = k)$ , where  $P_{\text{fake}}$  is a **Binomial** $(n, 1/5)$ .

A model of this problem is shown in Figure 6.16, where  $\#6's$  depends on  $\#rolls$  and  $Fake\_die?$ . Now, if we let  $\#rolls$  be interpreted as a numbered variable with state space  $\{1, 2, 3, 4, 5\}$ , let  $Fake\_die?$  be interpreted as a Boolean variable, and let  $\#6's$  be interpreted as a numbered variable with state space  $\{0, 1, 2, 3, 4, 5\}$ , then  $P(\#6's | \#rolls, Fake\_die?)$  can be specified elegantly using the expression

$$P(\#6's | \#rolls, Fake\_die?) = \text{Binomial}(\#rolls, \text{if}(Fake\_die?, 1/5, 1/6)).$$

Filling in the probabilities by hand would require computation of 60 values of the Binomial function with different parameters; see Table 6.5.



**Fig. 6.16.** A model for the fake die problem.

Fake_die?	#rolls	#6's					
		0	1	2	3	4	5
false	1	0.8333	0.1666	0	0	0	0
false	2	0.6944	0.2777	0.0277	0	0	0
false	3	0.5787	0.3472	0.0694	0.0046	0	0
false	4	0.4822	0.3858	0.1157	0.0154	0.0007	0
false	5	0.4018	0.4018	0.1607	0.0321	0.0032	0.0001
true	1	0.8	0.2	0	0	0	0
true	2	0.6400	0.3200	0.0400	0	0	0
true	3	0.5120	0.3840	0.0960	0.0080	0	0
true	4	0.4096	0.4096	0.1536	0.0256	0.0016	0
true	5	0.3276	0.4096	0.2048	0.0512	0.0064	0.0003

**Table 6.5.** The CPT for  $P(\#6's | \#rolls, Fake\_die?)$  in the fake die problem of Example 6.16 generated from the expression  $\text{Binomial}(\#rolls, \text{if}(Fake\_die?, 1/5, 1/6))$ .

*Example 6.17 (Discretization of a Random Variable (Hugin 2006)).* Assume that  $P(C_1 | C_2)$  can be approximated by a Normal distribution with mean given by  $C_2$  and with variance 1, where  $C_2$  is an interval variable with states  $]-5; -1], ]-1; 0], ]0; 1], ]1; 5]$ . If the discretization of  $C_1$  given by the intervals  $]-\infty; -5], ]-5; -2], ]-2; 0], ]0; 2], ]2; 5], ]5; \infty[$  is found to be suitable, then we can specify  $P(C_1 | C_2)$  simply as  $\text{Normal}(C_2, 1)$ . The probability distribution

$P(C_1 | C_2 = c_2)$  (i.e., the conditional distribution for  $C_1$  given that the value of  $C_2$  belongs to interval  $c_2$ ) is generated by computing a large number of probability distributions for  $C_2$ , each distribution being obtained by instantiating  $C_1$  to a value in the interval,  $c_2$ , under consideration. The average of these distributions (based on, for example, the midpoints of 25 subintervals) is used as  $P(C_1 | C_2 = c_2)$ . Hence, for expressions involving several interval variables as parents, the generation of the CPT may be computationally intensive. Table 6.6 shows  $P(C_1 | C_2)$ .

$C_2$	$C_1$					
	$] - \infty; -5]$	$] - 5; -2]$	$] - 2; 0]$	$] 0; 2]$	$] 2; 5]$	$] 5, \infty[$
$] - 5; -1]$	0.0996	0.6297	0.2499	0.0207	9.4E-5	3.8E-11
$] - 1; 0]$	7.1E-6	0.0748	0.6096	0.3075	0.0081	5.3E-8
$] 0; 1]$	5.3E-8	0.0081	0.3075	0.6096	0.0748	7.1E-6
$] 1; 5]$	3.8E-11	9.4E-5	0.0207	0.2499	0.6297	0.0996

**Table 6.6.** The CPT for  $P(C_1 | C_2)$  in the discretization problem of Example 6.17 generated from the expression `Normal( $C_2$ , 1)`.

## 6.6 Concluding Remarks

In this chapter we have tried to convey a set of good practices, routines, and hints that can be helpful for novices wanting to construct a probabilistic network model for a problem domain.

When constructing a model (probabilistic or not) it is crucial to realize that real-world problem domains are usually embedded in a complex reality involving interaction with numerous different aspects of the real world in a way that can never be fully captured in a model. Also, the internal causal mechanisms of a problem domain can almost always only be approximately described in a model. Thus, it is important to bear in mind that *all models are wrong*, but that some might be useful.

Based on this insight, it is important to clearly state the context of the model as well as the assumptions and conditions under which it is supposed to work. Real-world problem domains exist in an open world, whereas models for the problem domains are based on a (most often, erroneous) closed-world assumption.

The construction of a probabilistic network typically runs through four main phases:

Design of the network structure, covering identification of variables and (causal) relations among the variables. In addition, verification of the network structure is an essential activity of the design phase, where

the dependence and independence relations represented in the model are stated and verified.

Implementation of the network, covering the process of populating the CPTs and UTs with (conditional) probabilities and utilities. This phase is often the most labor intensive of the four phases.

Test of the network to check if it provides sensible outputs to a carefully selected set of inputs. In a medical setting, for example, testing may amount to entering patient data and comparing network recommendations (e.g., diagnoses or treatment plans) with recommendations provided by medical experts. If the test phase does not reveal any flaws of the network, construction of the network is considered successfully completed.

Analysis of the network is performed to pinpoint problematic aspects of the network revealed in the test phase. Various tools may be brought into play, including conflict analysis (see Chapter 9), sensitivity analyses (see Chapter 10), and value-of-information analysis (see Chapter 11).

In the design phase it is crucial to clearly define the problem that is going to be addressed by the model, and to pay close attention to this problem definition when identifying the variables of the model. It is strongly recommended to keep the number of variables and (causal) relations among them to a minimum; only those variables and relations that are thought to have significant influences on the problem variable(s) should be included.

In his writings, William of Occam (or Ockham) (1284–1347) stressed the Aristotelian principle that entities must not be multiplied beyond what is necessary. This principle became known as *Occam's Razor* or the *law of parsimony*; a problem should be stated in its basic and simplest terms. In science, the simplest theory that fits the facts of a problem is the one that should be selected. This rule is interpreted to mean that the simplest of two or more competing theories is preferable and that an explanation for unknown phenomena should first be attempted in terms of what is already known.<sup>1</sup>

One argument why one should go for simpler rather than complex solutions to a problem lies in the fact that simpler solutions impose less assumptions about the problem (e.g., about dependences and independences), and hence postulate fewer hypothetical solutions. The underlying idea is thus that simpler solutions are more likely to be “correct”.

A key design principle applied in the construction of virtually any complex system is the principle of a modular top-down design in which the level of abstraction changes from the more abstract to the more concrete. To support a modular design approach clear descriptions of the interface mechanisms of the modules must be provided. Also, given clear interface descriptions, cooperation among sub-teams, reuse modules (submodels), and support for bottom-up design are made possible. There are several reasons why an object-oriented modeling approach (see Section 4.3), which facilitate exactly a modular model

---

<sup>1</sup> This paragraph is taken from [http://www.2think.org/occams\\_razor.shtml](http://www.2think.org/occams_razor.shtml)

construction approach that allows for both top-down and bottom-up design, is recommended for constructing large models:

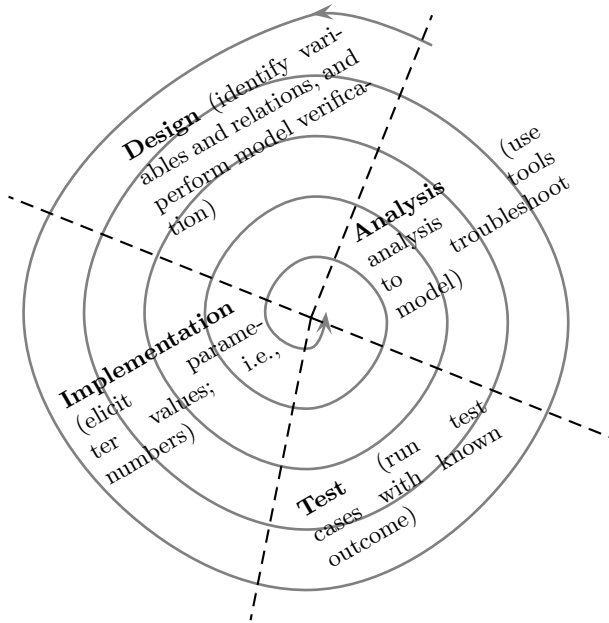
- Large and complex systems are often composed of collections of identical or similar components. Therefore, models of such systems will naturally contain repetitive submodels. Object orientation allows such components to be instantiated from a generic class. Both construction and maintenance becomes a whole lot easier in this way: each component is generated simply through instantiation and changes that apply to all instances should be made only in the class from which the components have been instantiated.
- Many complex real-world systems (e.g., mechanical and biological systems) are naturally described in terms of hierarchies of components (i.e., the system consists of components, which consist of sub-components, etc.). Thus, often an object-oriented probabilistic network (OOPN) more naturally describes the structure of the system modeled.
- Object-oriented model construction supports both top-down and bottom-up modes of construction, which are often used, respectively, to maintain a good overview of the model by abstracting away irrelevant details and to focus on sub-components with a well-defined interfaces to their surroundings. Thus, the OOPN framework provides support for working with different levels of abstraction in the model constructing process.
- Object-oriented model construction provides a natural means to reuse of existing sub-models. That is, the methodology provides a means to maintain a library of sub-models that can be instantiated in many different OOPNs.
- Specifying a model in a hierarchical fashion often makes the model less cluttered, and thus provides a better means of communicating ideas among knowledge engineers, domain experts, and users.
- The composition of a model by a number of components with well-defined interfaces supports a collaborative model construction process, where different model constructors work on different parts of the model.

Finally, it is important to realize that construction of a probabilistic network is an iterative process in the sense that if model testing reveals flaws of the model, another cycle through the model construction phases mentioned above is necessary. In most practical model construction projects, many iterations are needed before a workable model is found. This iterative process is illustrated in Figure 6.17.

## 6.7 Summary

Manual construction of a probabilistic network for a complex decision or diagnosis problem is usually a demanding task, involving different sources of expertise that provide model engineering skills as well as deep understanding of the problem domain. The model elicitation process requires careful





**Fig. 6.17.** Model construction is an activity that iteratively passes through design, implementation, test, and analysis phases until model tests no longer uncover undesired behavior of the model.

problem definition, careful identification of the relevant variables and dependences/independences among the variables, and elicitation of many (conditional) probabilities and utilities.

However appealing a probabilistic network might seem in terms of compactness of representation and in terms of serving as an intuitive means for communication of problem domain characteristics, there exist problems for which probabilistic networks are not the ideal tool to use. In Section 6.1, we discussed some characteristics of probabilistic networks and some criteria for using them. Briefly, and most importantly, the variables of the problem domain should be well-defined, causal relations among the variables should be identifiable, uncertainty should be associated with the causal relations, and the problem should contain an element of decision making with a desire to maximize the expected utility of a decision.

In Section 6.2, we discussed how to identify the right set of variables of a probabilistic network and what it takes for a variable to be well-defined. A simple taxonomy of variables was introduced, which includes three basic types of variables and their causal relations. Problem variables (or hypothesis variables) represent the diagnoses, classifications, predictions, decisions, etc. to be made. Information variables represent the available information (evidence) that can provide information relevant for solving the problem. Finally, mediating variables represent unobservable entities of the problem domain for

which posterior probabilities are of no immediate interest, but which play an important role for achieving the right dependence and independence properties of the network or for making efficient inference.

In Section 6.3, we first described a basic approach to structure elicitation, showing how the variable taxonomy can be used in the attempt to elicit the model structure. Next, we described how the notion of idioms can be helpful in identifying fractions of a network structure, depending on the nature of the semantic relations that exist among a small set of variables. Five idioms, thought to cover the vast majority of commonly occurring semantic relationships, were presented. The five idioms can be thought of as five archetypical modes of uncertain reasoning, and thus, using the idioms approach to elicitation of model structure, one is encouraged to think at a higher level of abstraction, leaving behind details about which links to include and their directionality.

Although the basic approach to structure elicitation can be quite feasible for some problems, for most (large) real-world problems the use of idioms is preferable, as the idioms approach splits the problem into smaller and more manageable chunks.

In Section 6.4 we briefly touched upon the issue of model verification, an important activity immediately following the structure elicitation effort. In the model verification process one checks if the dependence and independence statements imposed by the structure are consistent with the knowledge of problem domain experts.

In Section 6.5, we presented some techniques that might be considered in the attempt to elicit the (subjective) values of the parameters (i.e., (conditional) probabilities and utilities) dictated by the structure of the model. Also, we presented a lower-level taxonomy for variables, distinguishing among them in terms of their types of domains. Knowledge about the types of domains of variables allows for automatic generation of CPTs and UTs through a language of mathematical operations, including if-then-else statements, arithmetic and Boolean operations, and a variety of discrete and continuous distributions. The ability to define CPTs and UTs in terms of compact mathematical expressions might greatly reduce the burden of eliciting the numbers (parameter values) of a probabilistic network.

We concluded the discussion on model elicitation in Section 6.6 by pointing out some typical main phases of the model construction process, and how these phases are repeated iteratively until model tests no longer uncover undesired behavior of the model. Also, we pointed to the fact that the best models are usually constructed through deliberate use of the law of parsimony (or Occam's razor). Finally, we touched upon the potential benefits of applying an objected-oriented modeling approach, which facilitates modular model construction with the freedom to use a top-down or a bottom-up approach. The use of an object-oriented approach is especially beneficial for construction of large models.

## Exercises

**Exercise 6.1.** There are three condemned prisoners A, B and C. The governor has announced that one of the three, chosen at random, has been pardoned, but does not say which. Prisoner A, realizing that he only has a  $1/3$  chance of having been pardoned, reasons with the warden as follows: “Please tell me the name of one of the other prisoners B or C who will be executed. I already know that at least one of them will be executed so you will not be divulging any information.” The warden then asks how he should choose between B or C in case both are to be executed. “In that case,” A tells him, “simply flip a coin (when I’m not around) to choose randomly between the two.” The warden agrees and later tells A that B will be executed. On hearing this news, A smiles and thinks to himself, “Now my chances of having been pardoned have increased from  $1/3$  to  $1/2$ ”.

- Identify the variables of a Bayesian network model of the reasoning made by prisoner A.
- Specify the domains of the variables.
- Are your variables well-defined? Why or why not?
- Characterize the variables in terms of the taxonomy presented in Section 6.2.2 on page 150 and specify the causal links of your model using the prototypical causal structure shown in Figure 6.3.
- Specify the (conditional) probabilities of your model and check if your model agrees with the conclusion drawn by prisoner A.

**Exercise 6.2.** In Exercise 6.1, consider the suggestion to define three variables A, B, and C to represent the three prisoners. Are these variables well-defined? If so, why? If not, why not?

**Exercise 6.3.** In the morning when Mr Holmes leaves his house he realizes that his grass is wet. He wonders whether it has rained during the night or whether he has forgotten to turn off his sprinkler. He looks at the grass of his neighbors, Dr Watson and Mrs Gibbon. Both lawns are dry and he concludes that he must have forgotten to turn off his sprinkler.

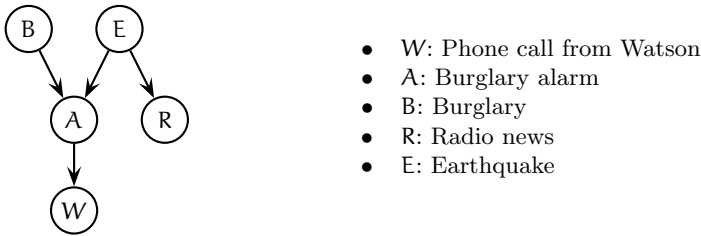
- Identify the relevant variables a probabilistic network representing Mr Holmes’ reasoning problem. Also, identify the domains of the variables.
- Characterize the variables in terms of the taxonomy presented in Section 6.2.2 on page 150 and specify the causal links of your model using the prototypical causal structure shown in Figure 6.3.
- If you were to construct the model using the idioms approach, which idiom(s) would you use?
- Verify that your model is consistent with the following dependence and independence statements:
  - Information about the states of the lawns (i.e., wet or dry) are independent if we know that it has rained; otherwise, they are dependent.

- (ii) Information about the state of rain and information about the state of Holmes' sprinkler are dependent if the state of Holmes' lawn is known; otherwise, they are independent.

**Exercise 6.4.** Consider the inference problem in Example 2.4 on page 25, which is stated as follows:

Mr Holmes is working in his office when he receives a phone call from his neighbor Dr Watson, who tells him that Holmes' burglar alarm has gone off. Convinced that a burglar has broken into his house, Holmes rushes to his car and heads for home. On his way, he listens to the radio, and in the news it is reported that there has been a small earthquake in the area. Knowing that earthquakes have a tendency to turn burglar alarms on, he returns to his work.

The structure of a Bayesian network for this inference problem is shown in Figure 6.18.



**Fig. 6.18.** Structure of a Bayesian network for the “Burglary or Earthquake” inference problem.

- (a) Classify the variables in Figure 6.18 according to the taxonomy in Section 6.2.2 on page 150.
- (b) Verify that the structure in Figure 6.18 is consistent with the prototypical causal structure shown in Figure 6.3 on page 153.

**Exercise 6.5.** Consider the task of providing your subjective probabilities of who is going to win the next World Cup in soccer.

- (a) Provide your probability that Brazil wins.
- (b) Consider the following gambles:
- (i) If Brazil wins, you receive \$10.
  - (ii) If you draw a red ball from an urn with  $n$  red balls and  $100 - n$  white balls, you receive \$10.

For which value of  $n$  are the two gambles equally attractive to you?

- (c) Compare your original subjective probability that Brazil wins with  $n/100$  from (b).

## Modeling Techniques

In this chapter we introduce a set of modeling methods and techniques for simplifying the specification of a probabilistic network.

The construction of a probabilistic network may be a labor-intensive task to perform. The construction involves a sequence of steps such as identifying variables, identifying states of variables, encoding dependence and independence relations as an acyclic, directed graph, and eliciting (conditional) probabilities and utilities as required by the structure of the acyclic, directed graph.

There are many reasons for considering the utilization of modeling techniques in the model development process. Modeling techniques may be applied in order, for instance, to simplify knowledge elicitation and model specification, capture certain properties of the problem domain that are not easily captured by an acyclic, directed graph, to reduce model complexity and improve efficiency of inference in the model, and so on.

Section 7.1 considers modeling techniques for adjusting the structure of a probabilistic network. This includes, in particular, modeling techniques that captures certain structural properties of the problem domain that help reduce the complexity of a model. Section 7.2 considers modeling techniques for the specification of conditional probability distributions. This includes modeling techniques for capturing uncertain information and for reducing the number of parameters to specify. Finally, Section 7.3 considers modeling techniques for influence diagram models. This includes modeling techniques of capturing properties of a problem domain that seemingly do not fulfill the underlying assumptions of influence diagrams.

### 7.1 Structure Related Techniques

In this section we consider modeling techniques related to the structure of a probabilistic network. In particular we consider parent divorcing, temporal transformation, the representation of structural and functional uncertainty,

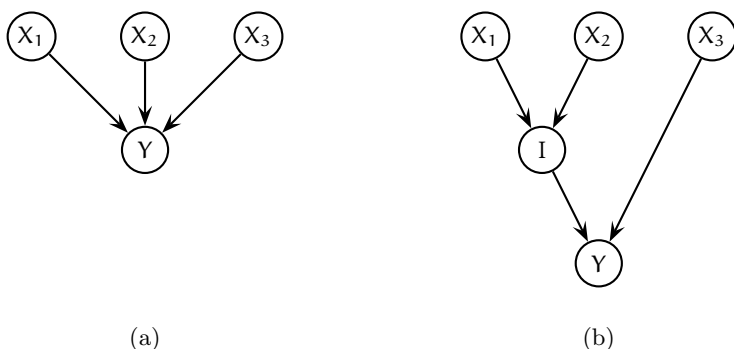
undirected dependence links, bidirectional relations, and the Naive Bayes model.

### 7.1.1 Parent Divorcing

The modeling techniques referred to as *parent divorcing* (Olesen, Kjærulff, Jensen, Jensen, Falck, Andreassen & Andersen 1989) is a commonly used modeling technique for reducing the complexity of a model by adjusting the structure of the graph of a probabilistic network. The technique of parent divorcing can be applied to reduce the complexity of specifying and representing the direct impact of a relatively large number of variables  $X_1, \dots, X_n$ , referred to as the *cause variables*, on a single variable  $Y$ , referred to as the *effect variable*.

The basic idea of parent divorcing is to introduce layers of intermediate variables between the effect variable  $Y$  and its direct causes  $X_1, \dots, X_n$  such that each intermediate variable  $I$  captures the impact of its parents on the child variable. The parents of  $I$  may consists of a subset of intermediate variables and cause variables.

Figure 7.1(a) illustrates a model structure where the variable  $Y$  has three direct parent causes  $X_1, X_2, X_3$ . Parent divorcing applied to  $Y$  and its direct causes  $X_1, X_2, X_3$  amounts to introducing a mediating variable  $I$  between  $Y$  and a subset of its parents  $X_1, X_2, X_3$ . Let the subset of parents be  $X_1$  and  $X_2$  such that  $Y$  after parent divorcing has parents  $X_3$  and  $I$  while  $X_1$  and  $X_2$  are parents of  $I$ . The result of this process is as illustrated in Figure 7.1(b). Notice that  $X_1$  and  $X_2$  are *divorced* from the remaining parents of  $Y$ .



**Fig. 7.1.** (a)  $X_1$ ,  $X_2$ , and  $X_3$  are direct parents of  $Y$ . (b)  $X_3$  is a direct parent of  $Y$  while the combined influence of  $X_1$  and  $X_2$  is mediated through  $I$ .

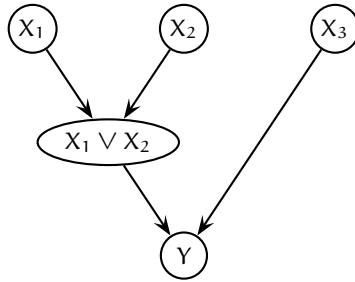
The following example illustrates how the use of parent divorcing may reduce the size of a conditional probability distribution significantly by exploiting structure within conditional probability distributions.

*Example 7.1.* Consider Figure 7.1 and assume  $Y$  is defined as the disjunction of its three parents  $X_1$ ,  $X_2$ , and  $X_3$ . This implies that the conditional probability distribution  $P(Y|X_1, X_2, X_3)$  is defined as shown in Table 7.1.

$X_1$	$X_2$	$X_3$	$Y$	
			false	true
false	false	false	1	0
false	false	true	0	1
false	true	false	0	1
false	true	true	0	1
true	false	false	0	1
true	false	true	0	1
true	true	false	0	1
true	true	true	0	1

**Table 7.1.** The conditional probability distribution  $P(Y|X_1, X_2, X_3)$ .

By inspection of Table 7.1 it is clear that the conditional probability distribution  $P(Y|X_1, X_2, X_3)$  has a lot of structure. This structure can be exploited to reduce the size of the largest conditional probability distribution using parent divorcing.



**Fig. 7.2.** Parent divorcing applied to the distribution for  $Y = X_1 \vee X_2 \vee X_3$ .

The structure in Figure 7.1(a) defines  $Y$  as  $Y = X_1 \vee X_2 \vee X_3$  disregarding the fact that disjunction is a binary operator. On the other hand the structure shown in Figure 7.2 defines  $Y$  as  $Y = (X_1 \vee X_2) \vee X_3$  by introducing a mediating variable capturing the expression  $X_1 \vee X_2$ . The distribution  $P(X_1 \vee X_2 | X_1, X_2)$  is shown in Table 7.2 (the distribution  $P(Y | X_1 \vee X_2, X_3)$  is equivalent).

Thus, instead of having one distribution of size 16 we have two tables of size 8. The reduction in size of the largest conditional probability table may seem insignificant. However, if there is a large number of parents the reduction is significant. The reduction may make an otherwise intractable task tractable.

$X_1$	$X_2$	$X_1 \vee X_2$	
		false	true
false	false	1	0
false	true	0	1
true	false	0	1
true	true	0	1

**Table 7.2.** The conditional probability distribution  $P(X_1 \vee X_2 | X_1, X_2)$ .

The fundamental idea of parent divorcing is that through the utilization of mediating variables it may be possible to divorce subsets of parents of the effect variable in order to limit the size of parent sets. Parent divorcing is almost only used when the relation among parent variables can be expressed as a chain of associative binary operations such as  $\vee, \wedge, \min, \max, +, -, \dots$

In general, the underlying assumption of parent divorcing is that the configurations of  $(X_1, X_2)$ , i.e., pairs of instantiations of  $X_1$  and  $X_2$ , can be partitioned into sets  $i_1, \dots, i_m$  such that different configurations  $(x_1, x_2), (x'_1, x'_2) \in i_i$  if and only if for all  $y$ :

$$P(y | x_1, x_2, x_3, \dots, x_n) = P(y | x'_1, x'_2, x_3, \dots, x_n)$$

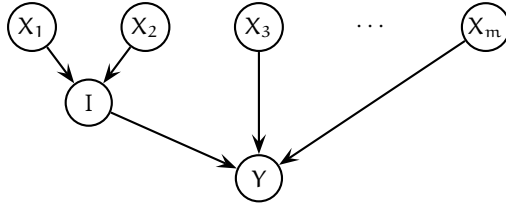
Table 7.3 shows how the conditional distribution  $P(Y | X_1, \dots, X_m)$  may support the use of parent divorcing. For different configurations of  $X_1$  and  $X_2$ , the child variable  $Y$  has the same distribution, e.g., for configurations  $(x_1, x_2)$  and  $(x'_1, x'_2)$ , the distribution of  $Y$  is  $z_1, \dots, z_n$ .

$X_1$	$X_2$	$X_3$	$\dots$	$X_m$	$Y$		
					$y_1$	$\dots$	$y_n$
$x_1$	$x_2$	$x_3$	$\dots$	$x_m$	$z_1$	$\dots$	$z_n$
		$\vdots$				$\vdots$	
$x_1$	$x'_2$	$x_3$	$\dots$	$x_m$	$z'_1$	$\dots$	$z'_n$
		$\vdots$				$\vdots$	
$x'_1$	$x_2$	$x_3$	$\dots$	$x_m$	$z'_1$	$\dots$	$z'_n$
		$\vdots$				$\vdots$	
$x'_1$	$x'_2$	$x_3$	$\dots$	$x_m$	$z_1$	$\dots$	$z_n$

**Table 7.3.** The conditional probability distribution  $P(Y | X_1, \dots, X_m)$ .

An intermediate variable  $I$  may be introduced in order to exploit of the structure of  $P(Y | X_1, \dots, X_m)$ . Figure 7.3 illustrates how the intermediate variable  $I$  is introduced as a parent of  $Y$  and a child of  $X_1$  and  $X_2$ .





**Fig. 7.3.** Parent divorcing in general.

The conditional probability distribution of the intermediate variable  $I$  is often a deterministic function in configurations of its parents. Table 7.4 shows the conditional probability distribution  $P(I|X_1, X_2)$ .

$X_1$	$X_2$	$I$	
		$i_1$	$i_2$
$x_1$	$x_2$	1	0
$x_1$	$x'_2$	0	1
$x'_1$	$x_2$	0	1
$x'_1$	$x'_2$	1	0

**Table 7.4.** The conditional probability distribution  $P(I|X_1, X_2)$ .

Since  $I$  replaces  $X_1$  and  $X_2$  as parents of  $Y$ , the conditional probability distribution of  $Y$  changes. Table 7.5 shows the conditional probability distribution  $P(Y|I, X_3, \dots, X_m)$ .

$I$	$X_3$	$\dots$	$X_m$	$Y$		
				$y_1$	$\dots$	$y_n$
$i_1$	$x_3$	$\dots$	$x_m$	$z_1$	$\dots$	$z_n$
		$\vdots$			$\vdots$	
$i_2$	$x_3$	$\dots$	$x_m$	$z'_1$	$\dots$	$z'_n$

**Table 7.5.** The conditional probability distribution  $P(Y|I, X_3, \dots, X_m)$ .

The above property is captured by introducing a mediating variable  $I$  as parent of  $Y$  with  $X_1$  and  $X_2$  as parents. Parent divorcing is particularly useful in situations where the state space size of the intermediate variable is (significantly) smaller than the combined state space of its parents. Example 7.1 on page 179 shows one situation where parent divorcing improves the efficiency of a model. That is, parent divorcing is (representationally) efficient if

$\|I\| < \|X_1\| \cdot \|X_2\|$ , i.e., if the number of subsets is less than the combined state space size of  $X_1$  and  $X_2$ .

Parent divorcing may be considered as a relevant modeling technique when specifying  $P(Y|X_1, \dots, X_n)$  is a significant or even intractable knowledge acquisition task or when the size of  $n$  makes probabilistic inference intractable.

Notice that parent divorcing can always be applied to a variable and its parents. If the intermediate variable  $I$  in Figure 7.1(b) has one state for each configuration of its parents, then the conditional probability distribution  $P(Y|X_3, I)$  can be considered as equivalent to  $P(Y|X_1, X_2, X_3)$ . In this case nothing has been gained from applying parent divorcing with respect to reducing the complexity of the model or improving efficiency of the model.

### How to Implement This Technique

The parent divorcing modeling technique is implemented as follows.

- (1) Let  $\mathcal{X}_W \subset \text{pa}(Y)$  be the subset of parents of  $Y$  to be divorced from  $\text{pa}(Y) \setminus \mathcal{X}_W$ .
- (2) Create an intermediate node  $I$  as a common child of  $\mathcal{X}_W$  and a new parent of  $Y$  replacing  $\mathcal{X}_W$  as parents of  $Y$ .
- (3) Let  $I$  have one state for each subset of  $\mathcal{X}_W$  mapping to the same distribution on  $Y$ .
- (4) Define the distribution of  $I$  given  $\mathcal{X}_W$  such that each subset of  $\mathcal{X}_W$  mapping to the same distribution on  $Y$  maps to the same state of  $I$ .
- (5) Repeat the above steps for each subset  $\mathcal{X}_W \subset \text{pa}(Y)$  to be divorced from  $\text{pa}(Y) \setminus \mathcal{X}_W$ .

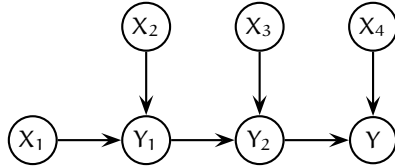
#### 7.1.2 Temporal Transformation

In this section we focus on applying the temporal transformation to adjust the network structure to capture structure within a conditional probability distribution of an effect variable  $Y$  given a set of causes  $X_1, \dots, X_n$  expressing a *temporal (or causal) order* on the impact of the cause variables on the effect variable  $Y$ . Instead of combining causes pairwise as in parent divorcing, the influence of causes on the effect variable are taken into account one cause at a time in their causal or temporal order.

The method of temporal transformation is best illustrated by an example. Figure 7.4 shows the result of applying the temporal order method on the conditional probability distribution of a variable  $Y$  given cause variables  $X_1, X_2, X_3$ , and  $X_4$ . Notice the temporal order on the causal impacts of the cause variables on the effect variable. The intermediate variables  $Y_1$  and  $Y_2$  have the same state spaces as  $Y$ .

The variables in Figure 7.4 may represent causes  $X_1, X_2$ , and  $X_3$  of a disease  $Y$  and a medicament  $X_4$  for curing the disease. The causes  $X_1, X_2$ , and  $X_3$  add to the level of the disease  $Y$  independently while the medicament

cures the disease no matter the level of the disease. In this example it is important that  $X_4$  is the last variable in the temporal order of the causes. The example could be extended such that  $X_1$ ,  $X_2$  and  $X_3$  represent different risk factors of the disease that have a temporal order.



**Fig. 7.4.** Modeling a temporal order of the impacts of  $X_1, \dots, X_4$  on  $Y$ .

The temporal transformation method was introduced by Heckerman (1993) and refined by Heckerman & Breese (1994). A temporal order of the causal impacts of  $X_1, \dots, X_n$  on  $Y$  is not necessary for applying the method of temporal transformation. In addition to representing a temporal order of causal influence, the temporal transformation method can be used as an alternative to parent divorcing. The parent divorcing method described in the previous section also captures internal structure of a conditional probability distribution of an effect variable given a set of cause variables. The parent divorcing method often constructs a (balanced) binary tree combining causes pairwise recursively, while the temporal transformation method constructs an unbalanced binary tree as illustrated in Figure 7.4.

The *temporal transformation* was introduced by Heckerman (1993) as a method for representing causal independence between a set of cause variables  $X_1, \dots, X_n$  with a common effect  $E$ . The model structure in Figure 7.1(a) on page 178 does not capture the property that cause variables  $X_1, \dots, X_n$  impact the effect variable  $E$  independently. Temporal transformation can be used to implement independence of causal influence as defined in Section 7.2.5.

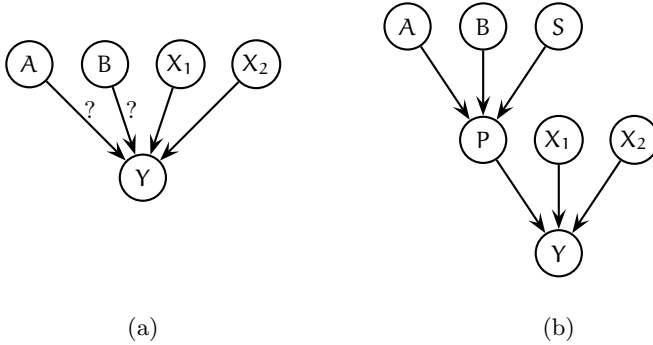
## How to Implement This Technique

The temporal transformation modeling technique is implemented as follows.

- (1) Let  $(X_1, \dots, X_n)$  be an ordering of the parents  $\text{pa}(Y)$  of  $Y$ .
- (2) For  $i = 2, \dots, n - 1$  create an intermediate node  $Y_i$  with the same state space as  $Y$  as a child of  $X_i$  and a parent of  $Y_{i+1}$  where  $Y_n = Y$ .
- (3) Add  $X_1$  as a parent of  $Y_2$ .
- (4) Define the distribution of  $Y_i$  for  $i = 2, \dots, n$  such that it captures the combined impact of its parents on  $Y$ .

### 7.1.3 Structural and Functional Uncertainty

When modeling certain domains as a probabilistic network it may be difficult or even seem impossible to specify the set of independence and dependence assumptions using a DAG. It may seem impossible to specify a static DAG for a problem domain where dependence relations change or are uncertain in the sense that they are not known at the time of model development. Similarly, it may be that the functional dependence relation between a variable and (a subset of) its parents is uncertain.



**Fig. 7.5.** (a) Should A or B be the parent of Y? (b) Modeling structure and functionality uncertainty.

Figure 7.5(a) shows an example where A and B may both be considered as parent of Y. However, due to the nature of the problem domain only one of the two is parent of Y at any given time. This is an example of what we term *structure uncertainty*. Figure 7.5(b) shows how this behavior may be represented as a DAG where S is a selector variable specifying P as taking on the value of A or B. The nodes A, B, and P are assumed to have the same domain, i.e.,

$$\text{dom}(A) = \text{dom}(B) = \text{dom}(P) = (z_1, \dots, z_n).$$

The prior distribution  $P(S = A) = 1 - P(S = B)$  specifies the prior belief in A being the true parent of Y. Table 7.6 shows the conditional probability distribution  $P(P|A, B, S)$ . We can define  $P(P|A, B, S)$  as

$$P = \begin{cases} A & \text{if } S = A \\ B & \text{if } S = B \end{cases}$$

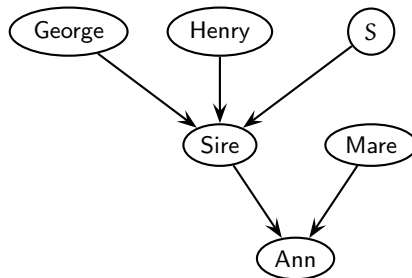
The following example illustrates how structure uncertainty between a variable Ann and two causes George and Henry may be represented.

S	A	B	P			
			$z_1$	$z_2$	$\cdots$	$z_n$
A	$z_1$	$z_1$	1	0	$\cdots$	0
A	$z_1$	$z_2$	1	0	$\cdots$	0
	$\vdots$				$\vdots$	
A	$z_2$	$z_1$	0	1	$\cdots$	0
A	$z_2$	$z_2$	0	1	$\cdots$	0
	$\vdots$				$\vdots$	
B	$z_1$	$z_1$	1	0	$\cdots$	0
B	$z_1$	$z_2$	0	1	$\cdots$	0
	$\vdots$				$\vdots$	
B	$z_2$	$z_1$	1	0	$\cdots$	0
B	$z_2$	$z_2$	0	1	$\cdots$	0
	$\vdots$				$\vdots$	

**Table 7.6.** The conditional probability distribution  $P(P|A, B, S)$ .

*Example 7.2 (Paternity).* In addition to maintaining his orchard Jack Fletcher breeds horses. Assume Jack — by mistake — placed a group of mares with two stallions (instead of a single stallion) for breeding. After some time the foal **Ann** is born. It is clear that the sire of **Ann** is one the stallions. The question is which one.

The two stallions are **Henry** and **George**. Soon after birth it is discovered that **Ann** is suffering from a disease caused by a certain genotype **aa**.



**Fig. 7.6.** Either **George** or **Henry** is the true sire of **Ann**.

This implies that one of the stallions is a carrier of the gene making its offspring unsuitable for breeding. A carrier of the disease has genotype **aA** while a pure horse has genotype **AA**. This stallion should not be used in future breeding. For this reason it is important to determine the paternity of **Ann**.

The graph shown in Figure 7.6 captures the properties of the problem. Each variable (except *S*) species the genotype of a horse where *Sire* denotes the *true* father of *Ann*.

S	Henry	George	Sire		
			aa	AA	aA
henry	aa	aa	1	0	0
henry	aa	AA	1	0	0
henry	aa	aA	1	0	0
	⋮			⋮	
george	aa	aa	1	0	0
george	aa	AA	0	1	0
george	aa	aA	0	0	1
	⋮			⋮	

**Table 7.7.** The conditional probability distribution  $P(\text{Sire}|\text{Henry}, \text{George}, S)$ .

The selector variable *S* specifies either *Henry* or *George* as the true father and its domain is  $\text{dom}(S) = (\text{henry}, \text{george})$ . Thus, the conditional probability distribution  $P(\text{Sire}|\text{George}, \text{Henry}, S)$  is defined as

$$\text{Sire} = \begin{cases} \text{Henry} & \text{if } S = \text{henry} \\ \text{George} & \text{if } S = \text{george} \end{cases}$$

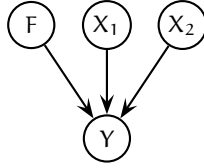
This construction can be generalized for more complex pedigrees with multiple generations and offspring of the stallion. Table 7.7 shows the conditional probability distribution  $P(\text{Sire}|\text{Henry}, \text{George}, S)$  where *aa*, *aA*, and *AA* are the three different genotypes.

The situation where a variable *Y* is a function of a subsets of its parents such that the state of *Y* is either one or another (known) function of its parents is termed *functional uncertainty*. Functional uncertainty is similar to structure uncertainty. The following example illustrates how functional uncertainty between a variable *Y* and two causes *X*<sub>1</sub> and *X*<sub>2</sub> may be represented.

*Example 7.3 (Functional Uncertainty).* Consider two Boolean variables *X*<sub>1</sub> and *X*<sub>2</sub>. Assume we know that there is a direct impact of configurations of *X*<sub>1</sub> and *X*<sub>2</sub> on the Boolean variable *Y*. Assume further that we know that either  $Y = X_1 \vee X_2$  or  $Y = X_1 \wedge X_2$  and that the first case is known to appear twice as frequently as the other.

This situation can be captured by a simplified version of the structure shown in Figure 7.5(b) as illustrated in Figure 7.7.

The state space of *F* is  $\text{dom}(F) = (\vee, \wedge)$  such that  $P(F) = (2/3, 1/3)$ . The conditional probability distribution of *Y* is defined as:



**Fig. 7.7.** Either  $Y = X_1 \vee X_2$  or  $Y = X_1 \wedge X_2$ .

$$Y = \begin{cases} \text{true} & \text{if } X_1 \vee X_2 \text{ and } F = \vee \\ \text{true} & \text{if } X_1 \wedge X_2 \text{ and } F = \wedge \\ \text{false} & \text{otherwise.} \end{cases}$$

F	$X_1$	$X_2$	Y	
			false	true
$\vee$	false	false	1	0
$\vee$	false	true	0	1
$\vee$	true	false	0	1
$\vee$	true	true	0	1
$\wedge$	false	false	1	0
$\wedge$	false	true	1	0
$\wedge$	true	false	1	0
$\wedge$	true	true	0	1

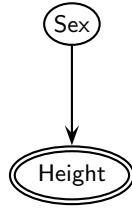
**Table 7.8.** The conditional probability distribution  $P(Y|F, X_1, X_2)$ .

This structure captures the uncertainty related to the impact of  $X_1$  and  $X_2$  on  $Y$ . Table 7.8 shows the resulting conditional probability distribution  $P(Y|F, X_1, X_2)$ .

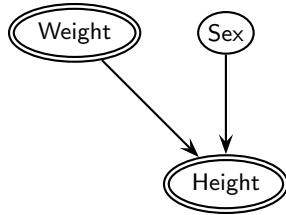
*Example 7.4.* In Example 4.10 on page 87 we have implicitly used the functional uncertainty modeling technique. In the example we assumed that the average height of a male person is greater than the average height of a female person. If the sex of a person is unknown to us when we want to reason about the height of the person, the situation is modeled using a simple variant of functional uncertainty as illustrated in Figure 7.8.

The example may be extended by assuming there is a correlation between height and weight as illustrated in Figure 7.9.

For each configuration of *Sex* we define a linear function between weight and height.



**Fig. 7.8.** Functional uncertainty on the height of a person.



**Fig. 7.9.** Functional uncertainty on the height of a person.

### How to Implement This Technique

The functional uncertainty modeling technique is implemented as follows.

- (1) Let  $Y$  be a random variable with parents  $\text{pa}(Y) = \{X_1, \dots, X_n\}$  such that  $Y$  is a function of  $\text{pa}(Y)$ .
- (2) Assume the functional dependence relation between  $Y$  and  $\text{pa}(Y)$  is uncertain such that the alternatives and their relative frequencies are known.
- (3) Create a discrete random variable  $F$  with one state for each possible functional dependence relation between  $Y$  and  $\text{pa}(Y)$ .
- (4) Define the prior probability distribution  $P(F)$  such that it encodes the relative frequency of the possible functional dependence relations.

The structure uncertainty modeling technique is implemented similarly to the way functional uncertainty is implemented.

#### 7.1.4 Undirected Dependence Relations

The DAG structure of a probabilistic network specifies a set of dependence and independence relations between variables. These dependence and independence relations are specified using directed links between pairs of variables only. When capturing a set of dependence relations between variables using a DAG it is not unusual to encounter the problem of how (most efficiently) to represent a dependence relation which by nature is undirected.



Let  $X_1$ ,  $X_2$ , and  $X_3$  be discrete variables with the same set of states. Assume configurations where all variables are in the same state are illegal. This is a typical example of an *undirected dependence relation* over a set of variables. This type of undirected relation is referred to as a *constraint*.

A constraint over a subset of variables may be enforced by introducing an auxiliary variable referred to as the *constraint variable* with an appropriate number of states as a child of the variables to be constrained. Often the constraint variable is Boolean, but it may have more than two states. Configurations of the parent variables are mapped to states of the child and the constraint is enforced using evidence on the constraint variable. For instance, assume that we want to enforce a prior joint probability potential  $f(X_1, X_2, X_3)$  over variables  $X_1$ ,  $X_2$ , and  $X_3$ . The joint probability can be enforced using a Boolean constraint node  $C$  with a conditional probability distribution defined as:

$$P(C = \text{on} | X_1, X_2, X_3) = f(X_1, X_2, X_3), \quad (7.1)$$

$$P(C = \text{off} | X_1, X_2, X_3) = 1 - f(X_1, X_2, X_3). \quad (7.2)$$

The constraint is enforced by instantiating  $C$  to *on*.

Figure 7.10 illustrates how constraints over configurations of variables  $X_1$ ,  $X_2$ , and  $X_3$  are enforced by introducing an auxiliary variable  $C$  with two states. One state reflects legal configurations of variables  $X_1$ ,  $X_2$ , and  $X_3$  while the other state reflects illegal configurations of variables  $X_1$ ,  $X_2$ , and  $X_3$ . In the example, all configurations where the three variables are not in the same state are legal, while the remaining configurations where all variables are in the same state are illegal. The constraint is enforced by instantiating the variable  $C$  to the state corresponding to legal configurations.

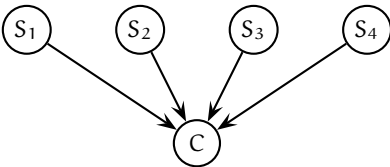


**Fig. 7.10.** (a) A functional relation  $f(X_1, X_2, X_3)$  is to be enforced. (b) A constraint over  $X_1$ ,  $X_2$ , and  $X_3$  is enforced by instantiating  $C$  to *on*.

The following example illustrates the application of the modeling technique described above to an everyday problem.

*Example 7.5 (Washing Socks (Jensen 1996)).* Two pairs of socks have been washed in the washing machine. The washing has been rather hard on the colors and patterns of the socks. One pair of socks is the pair of socks usually

worn to play golf why the other is the pair of socks usually worn during long airplane trips. The airplane socks help to improve blood circulation while the golf socks have improved respiration. For this reason it is important to pair the socks correctly.



**Fig. 7.11.** The constraint over  $S_1, \dots, S_4$  is enforced by instantiating  $C$  to on.

The airplane socks are blue while the golf socks are black. The patterns of two pairs of socks are also similar (at least after the washing).

S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	C	
				off	on
airplane	airplane	airplane	airplane	1	0
airplane	airplane	airplane	golf	1	0
airplane	airplane	golf	airplane	1	0
airplane	airplane	golf	golf	0	1
airplane	golf	airplane	airplane	1	0
airplane	golf	airplane	golf	0	1
airplane	golf	golf	airplane	0	1
airplane	golf	golf	golf	1	0
golf	airplane	airplane	airplane	1	0
golf	airplane	airplane	golf	0	1
golf	airplane	golf	airplane	0	1
golf	airplane	golf	golf	1	0
golf	golf	airplane	airplane	0	1
golf	golf	airplane	golf	1	0
golf	golf	golf	airplane	1	0
golf	golf	golf	golf	1	0

**Table 7.9.** The conditional probability distribution  $P(C|S_1, \dots, S_4)$ .

A model for distinguishing the socks of different types has to capture the undirected relation over the four socks. The relation enforces the fact that there are exactly two airplane socks and two golf socks.

The model has four variables  $S_1, \dots, S_4$ . Each  $S_i$  represents a sock and has domain  $\text{dom}(S_i) = (\text{airplane}, \text{golf})$ . The undirected relation  $R(S_1, \dots, S_4)$  is a constraint over configurations of the  $S_1, \dots, S_4$ . Figure 7.11 illustrates the

model structure while Table 7.9 shows the conditional probability distribution  $P(C|S_1, \dots, S_4)$ . The conditional probability distribution  $P(C|S_1, \dots, S_4)$  may be defined as

$$P(C = \text{on} | s_1, s_2, s_3, s_4) = \begin{cases} 1 & \text{if } |\{s_i = \text{airplane}\}| = 2 \\ 0 & \text{otherwise.} \end{cases}$$

The constraint is enforced by instantiating  $C$  to  $\text{on}$ .

In the description above we have focused on binary constraint variables. In the general case the constraint variable may have more than two states. In this case multiple states of the constraint variable specifying legal configurations can be enforced using likelihood evidence assigning the value zero to all states specifying illegal configurations and one to all states specifying legal configurations.

### How to Implement This Technique

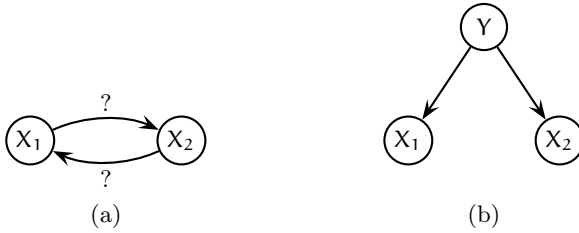
The undirected directions modeling technique is implemented as follows.

- (1) Let  $\{X_1, \dots, X_n\}$  be the set of variables over which the prior joint probability distribution  $f(X_1, \dots, X_n)$  is to be enforced.
- (2) Create a binary constraint node  $C$  with states  $\text{off}$  and  $\text{on}$ .
- (3) Add each  $X \in \{X_1, \dots, X_n\}$  as a parent of  $C$ .
- (4) Define the conditional probability distribution  $P(C|X_1, \dots, X_n)$  as specified in Equation 7.1 and Equation 7.2.
- (5) Instantiate  $C$  to state  $\text{on}$  enforcing the constraint.

#### 7.1.5 Bidirectional Relations

Section 7.1.4 describes how an undirected dependence relation over a subset of variables can be enforced using a constraint variable. The introduction of a constraint variable is necessary in order to represent the undirected relation as a DAG. In this section we consider the similar problem of representing what seems to be a bidirectional relation between a pair of variables. That is, when a pair of variables are dependent it is not always evident which direction the connecting link should have.

Figure 7.12(a) illustrates the situation where a pair of variables  $X_1$  and  $X_2$  should be connected by a link as there seems to be a direct dependence relation between  $X_1$  and  $X_2$ , but it is not possible to identify the direction of the link. Should the link be directed from  $X_1$  to  $X_2$  or vice versa? An insufficient set of variables for capturing the dependence and independence properties of a problem domain as a DAG is a common cause of this type of difficulty in identifying the direction of a link. Figure 7.12(b) illustrates how a mediating variable  $Y$  may be used to capture the bidirectional relation. The mediating variable  $Y$  is introduced as a common cause of  $X_1$  and  $X_2$ .



**Fig. 7.12.** (a) How should the bidirectional correlation between  $X_1$  and  $X_2$  be captured? (b) A mediating variable  $Y$  between  $X_1$  and  $X_2$  captures the bidirectional relation.

The following example illustrates how an insufficient set of variables for capturing the dependence properties of the problem domain can imply difficulties in determining the direction of links.

*Example 7.6 (Insemination (Jensen 1996)).* Consider the task of monitoring the pregnancy state of a cow (also considered in Example 6.5 on page 151). Assume we have the options to perform a blood test and a urine test to determine the pregnancy state of the cow. Both the blood test and the urine test are indicators for the pregnancy state of the cow. Furthermore, we argue that there is a dependence relation between the results of the two tests (if either is positive (negative) we would expect the other test to be positive (negative) as well).

We know there is a correlation between blood test and urine test, but we cannot identify one test as a cause of the other test. This is indicated in Figure 7.13(a) where  $Pr$  specifies the pregnancy state of the cow while  $BT$  and  $UT$  specify the results of the blood and urine tests, respectively. We assume the blood test is not independent of the urine test given the pregnancy state of the cow.

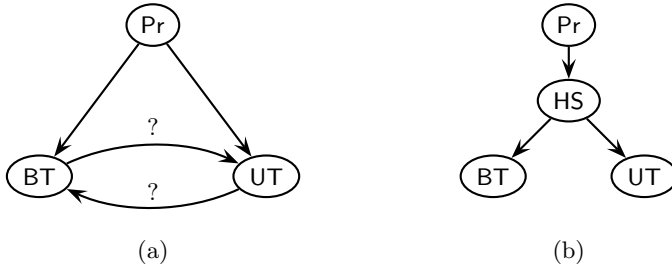
Looking deeper into the properties of the problem domain we identify some additional structure that alleviates the problem of a bidirectional relation between  $BT$  and  $UT$ . The two tests do not identify the pregnancy state of the cow directly. Instead the two tests identify the hormonal state of the cow. The resulting structure is shown in Figure 7.13(b) where  $HS$  represents the hormonal state of the cow.

Notice that the structure shown in Figure 7.13(b) correctly captures the conditional dependency of  $BT$  and  $UT$  given  $Pr$ .

## How to Implement This Technique

The bidirectional relations modeling technique is implemented as follows.

- (1) Let  $X_1$  and  $X_2$  be a pair of variables which seems to have a bidirectional interaction.



**Fig. 7.13.** (a) How should the bidirectional correlation between BT and UT be captured? (b) The bidirectional correlation between BT and UT is captured by the mediating variable HS.

- (2) Create a mediating variable  $Y$  such that it is the intermediate variable in a serial connection with  $X_1$  and  $X_2$ .
- (3) The identification of the states of  $Y$  and the probability distribution of  $Y$  is domain dependent.

### 7.1.6 Naive Bayes Model

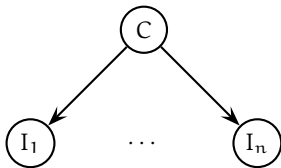
Restricted probabilistic graphical models are used or considered when low model complexity and high computational power are required. Low model complexity and high computational power is often required in classification related problems. In a classification problem the task is to classify an instance into a class based on observations on properties of the instance.

The Naive Bayes model is one of the simplest restricted probabilistic graphical models; see Friedman, Geiger & Goldszmidt (1997) who cite Duda & Hart (1973) and Langley, Iba & Thompson (1992). The Naive Bayes model is a popular model due to its high representational and computational simplicity while maintaining an impressive performance on classification tasks.

Since the Naive Bayes model is most commonly used for classification problems, we will describe the model from this point of view. We consider the task of classifying a set of instances into a predefined set of classes based on observations on properties of the instances. Let  $C$  be the class variable with one state for each possible class and let  $\mathcal{I} = \{I_1, \dots, I_n\}$  be the set of variables (also known as *attributes*, *indicators*, and *features*) where each variable represents a property that we can possibly observe and have decided to include in our model.

The structure of the Naive Bayes model is the reason for the simplicity and efficiency of the model. The structure of the Naive Bayes model is illustrated in Figure 7.14 where the class variable  $C$  is the only parent of each attribute and no other structure is present in the graph. The Naive Bayes model assumes

conditional pairwise independence of the attributes given the class. This is a rather strong, but often useful assumption.



**Fig. 7.14.** The structure of the Naive Bayes model.

The set of (conditional) probability distributions induced by the Naive Bayes model consists of the prior distribution  $P(C)$  on the class variable and the conditional probability distribution  $P(I_i|C)$  on the attribute  $I_i$  given the class for all  $i = 1, \dots, n$ . The Naive Bayes model induce a joint probability distribution over the class and attributes as:

$$P(\mathcal{X}) = P(C, I_1, \dots, I_n) = P(C) \prod_{i=1}^n P(I_i|C).$$

Notice that this implies that the representational complexity of the model is linear in the number of attributes.

Probabilistic inference in a Naive Bayes model consists of computing the conditional probability distribution  $P(C|\varepsilon)$  where  $\varepsilon$  consists of observations on a subset of the attributes of the instance to be classified. For any set of observations  $\varepsilon = \{i_1, \dots, i_m\}$  we may calculate the likelihood of the class as:

$$L(C|\varepsilon) = P(\varepsilon|C) = \prod_{i \in \varepsilon} P(i|C).$$

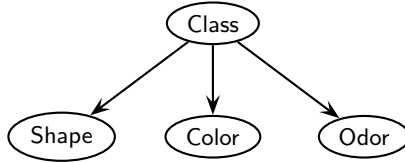
The posterior of the class is computed from the product of the prior and the likelihood by normalization  $P(C|\varepsilon) = \alpha L(C|\varepsilon)P(C)$ , where  $\alpha = P(\varepsilon)^{-1} = (\sum_C L(C|\varepsilon)P(C))^{-1}$ , or expressed via Bayes' rule as:

$$P(C|\varepsilon) = \frac{P(\varepsilon|C)P(C)}{P(\varepsilon)}.$$

Despite its simplicity and strong assumption of pairwise independence of the attributes given the class, the Naive Bayes model has in practice been shown to have excellent performance on (many) classification tasks. This makes the Naive Bayes model popular. The following example illustrates the most common application of the Naive Bayes model.

*Example 7.7.* Consider the task of classifying a mushroom as either edible or poisonous based on observations on the shape, color and odor of the mushroom. This is a classic classification problem. We make observations on the mushroom to identify it as either edible or poisonous.

Figure 7.15 shows a Naive Bayes model for this classification task. The model has class variable **Class** and feature variables **Color**, **Odor**, and **Shape**. The class variable is the direct parent of each feature variable and no other structure is present.



**Fig. 7.15.** A Naive Bayes model for classifying mushrooms.

The class variable has states  $\text{dom}(\text{Class}) = (\text{edible}, \text{poisonous})$  while the feature variables have states  $\text{dom}(\text{Odor}) = (\text{none}, \text{almond}, \text{spicy})$ ,  $\text{dom}(\text{Shape}) = (\text{flat}, \text{bell}, \text{convex})$ , and  $\text{dom}(\text{Color}) = (\text{brown}, \text{white}, \text{black})$ .

The prior distribution on **Class** specifies the frequency of edible and poisonous mushrooms while the conditional distribution of each feature variable specifies the distribution of the feature given the mushroom class. Table 7.10 shows the distribution  $P(\text{Odor}|\text{Class})$ . The distribution of each of the other feature variables is similar.

C	Odor		
	none	almond	spicy
edible	0.902	0.0979	0.0001
poisonous	0.173	0.001	0.826

**Table 7.10.** The conditional probability distribution  $P(\text{Odor}|\text{C})$ .

Each time a mushroom is picked up, the features of the mushroom are observed and entered into the model as evidence. After inference the model returns the probability that the mushroom is edible.

There exist other classes of restricted probabilistic graphical models than the Naive Bayes model. For instance, the Tree-Augmented Naive Bayes model (Friedman et al. 1997) appears as a natural extension of the Naive Bayes model while the Hierarchical Naive Bayes model (Zhang 2004) is another extension of the Naive Bayes model.

## How to Implement This Technique

The Naive Bayes modeling technique is implemented as follows.

- (1) Let  $C$  be the class variable with one state for each possible class.
- (2) Let  $\mathcal{I} = \{I_1, \dots, I_n\}$  be the set of feature variables.
- (3) Let  $C$  have no parents and let it be the only parent of each feature variable  $I_i$ . In this way,  $C$  becomes the intermediate variable in a serial connection with each pair of feature variables.
- (4) Define the prior probability distribution  $P(C)$  such that it encodes the relative frequency of each class.
- (5) For each  $I_i \in \mathcal{I}$  define the conditional probability distribution  $P(I_i|C)$  such that it encodes the relative frequency of each state of the feature given each state of the class variable.

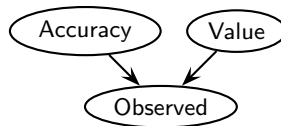
If data are available, then it may be an advantage to estimate the prior and conditional probability distributions  $P(C)$  and  $P(I_1|C), \dots, P(I_n|C)$  from data.

## 7.2 Probability Distribution Related Techniques

In this section we consider modeling techniques related to the specification of probability distributions of a probabilistic network. In particular we consider measurement error, expert opinions, node absorption, setting a value by intervention, independence of causal influence and mixture of Gaussian distributions.

### 7.2.1 Measurement Uncertainty

Probabilistic networks are well-suited models for reflecting properties of problem domains with some kind of uncertainty. The sources of uncertainty may be many and diverse. In this section we consider a modeling technique for representing uncertainty related to measurements. Measurements and observations on the state of the problem domain such as, for instance, sensor readings and noisy observations, are subject to uncertainty. In some situations it may be important to capture and represent the uncertainty explicitly in a probabilistic model.



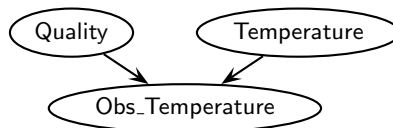
**Fig. 7.16.** The observed value of a phenomenon is a function of the measurement and the actual value of the measured phenomenon.

Figure 7.16 illustrates a modeling technique that captures measurement uncertainty. The variable **Value** represents the actual value of the phenomenon



being measured, the variables **Observed** and **Accuracy** represent the observed value of the phenomenon and the accuracy with which observations are made, respectively.

*Example 7.8.* For some reason we would like to measure the temperature in a room. The *true* temperature is unknown, but we may use a thermometer to get an estimate of the temperature in the room. Assume we have two different thermometers to choose from: one thermometer of low quality and another thermometer of high quality. The high quality thermometer offers more accurate estimates of the temperature.



**Fig. 7.17.** The measured temperature is a function of the quality of the thermometer and the actual temperature.

Figure 7.17 shows the structure of a model with variables **Obs\_Temperature**, **Quality**, and **Temperature**. Assume that the three variables have domains  $\text{dom}(\text{Obs\_Temperature}) = (\text{low}, \text{medium}, \text{high})$ ,  $\text{dom}(\text{Quality}) = (\text{low}, \text{high})$ , and  $\text{dom}(\text{Temperature}) = (\text{low}, \text{medium}, \text{high})$ . Table 7.11 shows the conditional probability distribution  $P(\text{Obs\_Temperature} | \text{Quality}, \text{Temperature})$ .

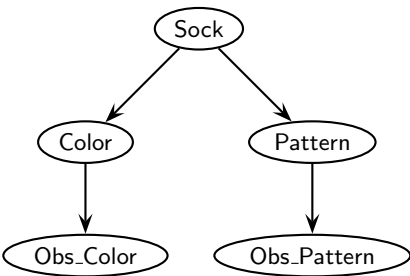
Quality	Temperature	Obs_Temperature		
		low	medium	high
low	low	0.6	0.3	0.1
low	medium	0.2	0.6	0.2
low	high	0.1	0.3	0.6
high	low	0.9	0.1	0
high	medium	0.05	0.9	0.05
high	high	0	0.1	0.9

**Table 7.11.** The conditional probability distribution  $P(\text{Obs\_Temperature} | \text{Quality}, \text{Temperature})$ .

Notice how the distribution over **Obs\_Temperature** depends on the quality of the thermometer used to measure the temperature. This reflects the accuracy of each thermometer.

An explicit representation of the accuracy with which observations are made is not always necessary.

*Example 7.9.* Example 7.5 on page 189 illustrates how to enforce the fact that there are two socks of each type (airplane and golf). To classify the four socks we make observations on the color and pattern of each sock. Color and pattern are indicator variables for the type of sock.



**Fig. 7.18.** The observations on color and pattern are imperfect.

The observations on color and pattern are imperfect due to the washing. Figure 7.18 shows the model structure for classifying a single sock based on (imperfect) observations on color and pattern.

Color	Obs_Color	
	blue	black
blue	0.9	0.1
black	0.05	0.95

**Table 7.12.** The conditional probability distribution  $P(\text{Obs\_Color}|\text{Color})$ .

The conditional probability distribution  $P(\text{Obs\_Color}|\text{Color})$  is shown in Table 7.12. Notice that **blue** is observed as **black** in 10% of the cases and **black** is observed as **blue** in 5% of the cases.

The measure uncertainty modeling technique is closely related to the measurement idiom, see Section 6.3.2 on page 154.

**How to Implement This Technique**

The measurement uncertainty modeling technique is implemented as follows.

- (1) Let variable **Value** represent the actual value of the phenomenon being measured.

- (2) Create variables **Observed** and **Accuracy** representing the observed value of the phenomenon and the accuracy with which observations are made, respectively.
- (3) Let **Value** and **Accuracy** be the parents of **Observed**.
- (4) Let **Observed** have one state for each possible observation of **Value**.
- (5) Let **Accuracy** have one state for each possible level of accuracy of the observation on **Value**.
- (6) Define the prior probability distribution  $P(\text{Accuracy})$  such that it encodes the relative frequency of each possible level of accuracy.
- (7) Define the conditional probability distribution  $P(\text{Observation}|\text{Accuracy}, \text{Value})$  such that it encodes the relative frequency of each possible observation given the level of accuracy and the actual value.

### 7.2.2 Expert Opinions

The specification of the parameters of a probabilistic network is often based on knowledge elicitation from problem domain experts. Typically, a knowledge engineer interviews one or more experts in order to assess the values of model parameters. In some cases when the elicitation of parameters is based on assessments from a group of experts, it is advantageous that any differences in the assessed values are represented explicitly in the model. This is, for instance, useful when the group of experts are distributed physically and when the model is developed iteratively.

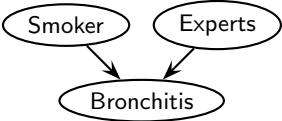
A conditioning (or auxiliary) variable can select among the opinions of different experts expressed in the probability assessments of a single variable. The conditioning variable is a parent of the variable of interest and has one state corresponding to each expert. The prior distribution of the auxiliary value will assign a weight to the experts represented in the auxiliary variable. Different auxiliary variables need not have the same set of states. The following example illustrates the modeling technique on a simple example.

*Example 7.10.* Consider the quantification of the Chest Clinic example (Example 4.2 on page 68). Assume the model is constructed by elicitation of knowledge from two experts Bill and John. Consider the elicitation of conditional probability distribution  $P(\text{Bronchitis}|\text{Smoker})$  and assume that Bill and John have different opinions on this distribution.

To reflect the different opinions of the experts, we construct the model structure shown in Figure 7.19 where  $\text{dom}(\text{Experts}) = (\text{bill}, \text{john})$  representing the two experts.

Table 7.13 shows the distribution  $P(\text{Bronchitis}|\text{Smoker}, \text{Experts})$ . The distribution encodes the different opinions of the experts on the conditional probability distribution whereas the prior distribution  $P(\text{Experts})$  encodes the reliability of the experts.

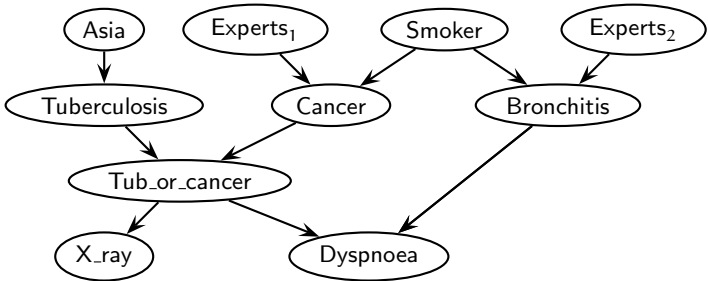
The model captures the opinions of experts Bill and John using the **Experts** variable to condition the conditional probability distribution they have different opinions on.



**Fig. 7.19.** The variable *Experts* has one state for each expert.

Experts	Smoker	Bronchitis	
		false	true
bill	false	0.7	0.3
bill	true	0.4	0.6
john	false	0.8	0.2
john	true	0.3	0.7

**Table 7.13.** The specification of the conditional probability distribution  $P(\text{Bronchitis}|\text{Smoker}, \text{Experts})$ .



**Fig. 7.20.** A graph specifying the independence and dependence relations of the Asia example.

One expert node is introduced for each conditional probability distribution elicited from domain expert knowledge. Figure 7.20 illustrates how two groups of experts have been consulted to elicit the conditional probability distributions of *Bronchitis* and *Cancer*. By introducing multiple expert nodes, we assume the elicitation of different conditional probability distributions to be independent.

The model in Example 7.10 has an explicit representation of the opinions of the two experts. In some situations it is desirable not to have an explicit representation of expert opinions in the model. This can be achieved by eliminating the variables representing different experts from the model. This is described in Section 7.2.3.

## How to Implement This Technique

The expert opinions modeling technique is implemented as follows.

- (1) Let  $P(X|pa(X))$  be the conditional probability distribution assessed from a group of experts (one instance of  $P(X|pa(X))$  is assessed from each expert).
- (2) Create a discrete random variable **Experts** with one state for each expert.
- (3) Let **Experts** be a parent of  $X$ .
- (4) Define the prior probability distribution  $P(\text{Experts})$  such that it encodes the reliability of the experts.
- (5) Define the conditional probability distribution  $P(X|pa(X), \text{Experts})$  such that for each state of **Experts** it encodes the assessment of  $P(X|pa(X))$  given by the corresponding expert.

### 7.2.3 Node Absorption

Node absorption is the process of eliminating a variable from a model by arc reversals and barren variable eliminations. Recall that in Section 3.4.1 on page 52 we illustrated the application of Bayes' rule as an arc reversal operation while in Section 5.1.1 on page 111 we considered repeated applications of arc reversal as an inference process.

The node absorption method may also be a useful tool in the model development process. Node absorption may be used to eliminate variables from a model which for one reason or another should not be included in the final model. If efficiency of probabilistic inference in a probabilistic network is of high priority, it may be worthwhile to eliminate variables that are neither observed nor the target of inference. In Section 5.1.1 we denoted a variable that is neither an evidence variable nor a target variable as a *nuisance variable*.

*Example 7.11 (Expert Opinions).* Consider Example 7.10 on page 199 where the conditional probability distribution  $P(\text{Bronchitis}|\text{Smoker})$  has been elicited from the two experts Bill and John. From the example we know that Bill and John disagree slightly on the strength of the dependence relation between **Bronchitis** and **Smoker**. This is captured by the graph of Figure 7.19.

For different reasons (e.g. political) we would like to eliminate the intermediate variable **Experts** from the model while maintaining the underlying dependence relations between the remaining variables. This can be achieved using node absorption.

Since **Experts** has **Bronchitis** as its only child, a single arc reversal operation is sufficient to absorb **Experts**. Once the arc (**Experts**, **Bronchitis**) is reversed, **Experts** is barren and can therefore be removed from the graph without changing the dependence relations between the remaining variables in the graph.

If we assume that we have equal trust in the two experts, then Table 7.14 shows the conditional probability distribution  $P(\text{Bronchitis}|\text{Smoker})$  after absorbing **Experts** from the distribution shown in Table 7.13.

Smoker	Bronchitis	
	false	true
false	0.75	0.25
true	0.35	0.65

**Table 7.14.** The conditional probability distribution  $P(\text{Bronchitis}|\text{Smoker})$  after absorbing Experts from the distribution shown in Table 7.13.

The prior distribution  $P(\text{Experts})$  can be interpreted as specifying our relative trust in the two experts. In the example we have used a uniform distribution.

The order in which arcs are reversed may be constrained by the structure of the graph. That is, the sequence of arc reversals should be performed such that all intermediate graphs are acyclic. In addition, the order in which variables are absorbed and arcs are reversed may impact the size of the parent sets in the resulting graph.

### How to Implement This Technique

The node absorption modeling technique is implemented as follows.

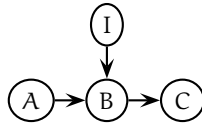
- (1) Let  $X$  be the variable to be eliminated by node absorption.
- (2) Let  $\text{ch}(X)$  be the direct successors of  $X$ , i.e., the children of  $X$ .
- (3) For each  $Y \in \text{ch}(X)$  reverse the link  $(X, Y)$  according to the arc reversal operation. Traverse  $\text{ch}(X)$  in topological order.
- (4) Eliminated  $X$  as a barren variable, i.e., simply remove  $X$  and incoming links from the model.

Node absorption may be implemented as a single step operation in probabilistic network editor software.

#### 7.2.4 Set Value by Intervention

An important distinction should be made between a passive observation of the state of a variable and an active action forcing a variable to be in a certain state. A passive observation of a variable impacts the beliefs of the ancestors of the variable whereas an active action enforcing a certain state on a variable does not under the assumption of a causal ordering (see Section 4.2 on decision making under uncertainty). We refer to this type of active action as an *intervention*. When we make a passive observation on a variable this produces a likelihood on the parents of the variable. This should not be the case when the value of a variable is set by intervention. The instantiation of a decision variable in an influence diagram is an example of this type of intervention.

In some situations it is undesirable to model active actions forcing a variable to be in a certain state as a decision in an influence diagram. Instead of modeling the situation using decision variables a simple modeling technique may be used. The modeling technique is illustrated in Figure 7.21.



**Fig. 7.21.** Modeling the option of setting a value of B by intervention.

In Figure 7.21 we illustrate a situation where the value of the random variable B may be set by intervention. The causal properties of the example are such that the variable A has a causal impact on B which in turn has a causal impact on C. The variable I captures the property that the state of variable B may be set by intervention. Assuming Table 7.15(a) shows the conditional probability distribution  $P(B|A)$ , then Table 7.15(b) shows the distribution  $P(B|A, I)$ .

A	B		I	A	B	
	false	true			false	true
false	0.9	0.1	no intervention	false	0.9	0.1
true	0.2	0.8	no intervention	true	0.2	0.8
			false	false	1	0
			false	true	1	0
			true	false	0	1
			true	true	0	1

(a)
(b)

**Table 7.15.** (a) The conditional probability distribution  $P(B|A)$ . (b) The conditional probability distribution  $P(B|I, A)$ .

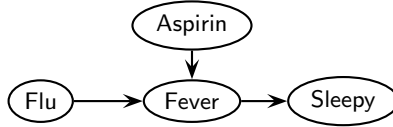
This construction of  $P(B|I, A)$  implies that  $C \perp\!\!\!\perp A|I = i$  where  $i \neq$  no intervention, i.e., setting I to a value different from no intervention makes A and C independent. Thus, if we enforce a certain state on B by selecting a state of I (different from no intervention), then observing C subsequently will not change the belief in A. In general, the conditional probability distribution  $P(B|I, A)$  may be defined as

$$P(B = b|A, I = i) = \begin{cases} P(b|A) & \text{if } i = \text{no intervention} \\ 1 & \text{if } b = i \\ 0 & \text{otherwise} \end{cases} \quad (7.3)$$

where  $\text{dom}(I) = \text{dom}(B) \cup \{\text{no intervention}\}$ .

It is important to notice that when the state of  $B$  is observed, the observation is enforced by setting the state of  $B$  whereas if the state of  $B$  is set by intervention, then  $I$  is instantiated to the corresponding state. When  $B$  is not observed,  $I$  is in the state **no intervention**.

*Example 7.12.* Figure 7.22 depicts a simple model for reasoning about a common medical situation. The model captures the direct causal influence of flu on fever and the direct causal impact of fever on sleepiness. These events are represented by the variables *Flu*, *Fever*, and *Sleepy*, respectively.



**Fig. 7.22.** Taking an aspirin forces the fever to a certain level. Subsequent observations on *Sleepy* should not change our belief in *Flu*.

In addition to the aforementioned variables, the model has the variable *Aspirin*. This variable represents the event that the patient takes an aspirin to reduce fever to a certain level. Once an aspirin has been taken an observation on *Sleepy* will be uninformative with respect to *Flu*. This behavior may be enforced as described above.

## How to Implement This Technique

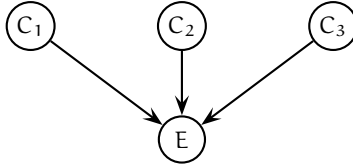
The set value by intervention modeling technique is implemented as follows.

- (1) Let  $X$  be the random variable that may be set by intervention.
- (2) Create a random variable  $I$  with  $\text{dom}(I) = \text{dom}(B) \cup \{\text{no intervention}\}$ .
- (3) Let  $I$  be a parent of  $X$ .
- (4) Define the prior probability distribution  $P(I)$  such that it encodes the relative frequency of setting each state of  $X$  and no intervention.
- (5) Define the conditional probability distribution  $P(X|\text{pa}(X), I)$  according to Equation 7.3.



### 7.2.5 Independence of Causal Influence

In this section we consider how a special kind of structure within a conditional probability distribution may be exploited to reduce the complexity of knowledge elicitation from exponential in the number of parents to linear in the number of parents. The property we consider is known as *independence of causal influence* (Heckerman 1993).



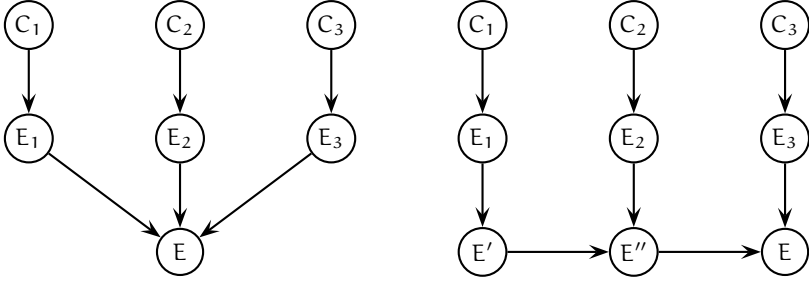
**Fig. 7.23.** The causal influence of  $C_i$  on  $E$  is independent of the causal influence of  $C_j$  on  $E$  (for  $i \neq j$ ).

In an independence of causal influence model, the parent variables of a common child variable interact independently on the child. With a slight abuse of terms, the parents are sometimes said to be *causally independent*. All variables in an independence of causal influence model are assumed to be discrete random variables. The common child variable is denoted  $E$  and it is referred to as the *effect variable*. The parent variables are denoted  $C_1, \dots, C_n$  and they are referred to as *cause variables* or *causes*, see Figure 7.23.

The cause variables  $C_1, \dots, C_n$  may cause an abnormality modeled as the effect variable  $E$  to be present at a certain level. The states of the effect variable  $E$  specify different levels of the abnormality. The states of  $E$  are ordered in the sense that they represent different levels of abnormality and such that a *designated state* indicates that the abnormality is absent. Similarly, each of the causes have an absence state corresponding to *no impact* on the effect variable. The principle of an independence of causal influence model is that the causal impact of each cause is independent of the causal impact of all other causes.

In this section we consider the Boolean independence of causal influence model known as the *Noisy-OR model* (Pearl 1988). The Noisy-OR model is a commonly used example of a model for local conditional probability distributions that depends on fewer parameters than the total number of combinations of  $\text{fa}(E)$  (Laskey 1993).

In the Noisy-OR model, the effect variable  $E$  and the variables  $C_1, \dots, C_n$  are Boolean variables (i.e., binary discrete random variables with states *false* and *true*). The designated state is *false*. The causal impact of each cause  $C_i$  is independent of the causal impact of any other cause  $C_j$  for  $i \neq j$ . Figure 7.24 illustrates two different ways in which this independence may be modeled explicitly. Each variable  $E_i$  has the same state space as  $E$  and it captures the



**Fig. 7.24.** Two model structures for capturing independence of causal influence.

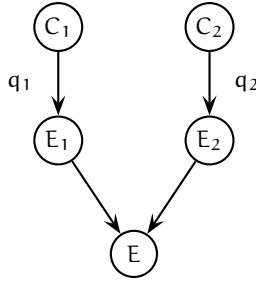
contribution from cause  $C_i$  to the value of  $E$ . Each variable  $E_i$  is referred to as a *contribution variable* and  $P(E_i|C_i)$  captures the causal impact of  $C_i$  on  $E$ . In the left part of the figure, the total impact on the effect variable is the disjunction of all causes whereas in the right part of the figure the temporal transformation modeling technique has been applied such the total impact is determined based on a pairwise combination of causes. The conditional probability distribution  $P(E|E_1, \dots, E_n)$  is defined as disjunction and so are  $P(E''|E', E_2)$  and  $P(E|E'', E_3)$ . The effect variable  $E$  is in state **true** when at least one contribution variable is in state **true**.

The causal impact of a cause  $C_i$  is the probability  $P(E = \text{yes}|C_i = \text{yes})$  whereas  $P(E = \text{yes}|C_i = \text{no}) = 0$ . We denote  $P(E = \text{yes}|C_i = \text{yes}) = 1 - q_i$  where  $q_i$  is referred to as the *inhibitor probability*, see Figure 7.25.

In some domains there may be a need to have a *leak probability*  $1 - q_0$  representing the probability of  $E = \text{true}$  when all causes  $C_1, \dots, C_n$  are absent where  $q_0$  is known as the *default inhibitor*. A leak probability may be implemented by introducing as a separate Boolean cause variable  $C_0$  instantiated to state **true**. The leak variable  $C_0$  represents the set of causes are not modeled explicitly in the network. In this way the leak variable can be used to enforce the closed-world assumption. The leak probability is assigned as the probability that the effect will occur in the absence of any of the causes  $C_1, \dots, C_n$  that are explicitly represented in the network (Pradhan, Provan, Middleton & Henrion 1994).

Let us consider how the reduction from exponential to linear in the number of parents is achieved. We may consider the conditional probability distribution  $P(X_i|\text{pa}(X_i))$  as parameterized over a vector  $\Theta_i$  of parameters  $\theta_{ijk}$  with one component for each possible value of  $X_i$  and combination of  $\text{pa}(X_i)$  such that

$$P(x_{ijk}|\pi_{ij}, \Theta_i) = \frac{\theta_{ijk}}{\sum_k \theta_{ijk}},$$



**Fig. 7.25.** One inhibitor probability for each parent  $C_i$  of the effect  $E$ .

where  $\pi_{ij}$  is the  $j$ th configuration of  $\text{pa}(X_i)$ . The above formula is an unrestricted local conditional probability distribution. The distribution depends on as many parameter vectors as there are combinations of  $\text{fa}(X_i)$ .

In an independence of causal influence model, the conditional probability distribution  $P(X_i | \text{pa}(X_i))$  can be specified using a parameter  $\Theta_i$  that grows in size linearly in the number of parents  $\text{pa}(X_i)$ .

For the Noisy-OR model it is straightforward to determine the conditional probability distribution  $P(E | \text{pa}(E), \Theta_E)$  given a specific parameter vector  $\Theta_E$  from the Noisy-OR model

$$P(E = \text{true} | X_1 = x_1, \dots, X_n = x_n, \Theta_E) = 1 - \theta_0 \prod_{X_i = \text{true}} \theta_i,$$

where  $\theta_0$  is the default inhibitor,  $\theta_i$  is the inhibitor for  $X_i$ , and  $\Theta_E = \{\theta_0, \theta_1, \dots, \theta_n\}$ . From this it follows that

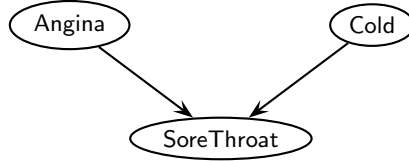
$$P(E = \text{false} | X_1 = x_1, \dots, X_n = x_n, \Theta_E) = \theta_0 \prod_{X_i = \text{true}} \theta_i.$$

The following example illustrates how independence of causal influence may be exploited to simplify the knowledge elicitation process.

*Example 7.13 (Sore Throat).* A physician wants to diagnose her patients with respect to diseases causing a sore throat. For simplicity of the example we assume the physician is mainly interested in modeling the causal effect of cold and angina on sore throat. In addition to cold and angina there are other potential causes of a sore throat. These other causes are not to be represented explicitly in the model though.

Thus, initially the model consists of three variables **SoreThroat**, **Angina**, and **Cold**. All variables are Boolean with states **false** and **true**. Figure 7.26 shows the structure of the model.

The synergy between **Angina** and **Cold** with respect to their combined effect on **SoreThroat** is assumed to be minimal. Thus, we may use the Noisy-OR model to specify and represent the conditional probability distribution



**Fig. 7.26.** Sore throat may be caused by both angina and cold.

of SoreThroat given Angina and Cold where all other implicit causes of sore throat are captured by the background event.

First, assume the inhibitor probabilities are  $q_{\text{Angina}} = 0.1$  and  $q_{\text{Cold}} = 0.2$  while the default inhibitor is one (i.e., there are no other causes of sore throat). The combined impact of Angina and Cold on SoreThroat is computed as

$$\begin{aligned}
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{false}, \text{Cold} = \text{false}, \Theta_E) &= 1, \\
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{false}, \text{Cold} = \text{true}, \Theta_E) &= 0.2, \\
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{true}, \text{Cold} = \text{false}, \Theta_E) &= 0.1, \\
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{true}, \text{Cold} = \text{true}, \Theta_E) &= 0.1 * 0.2.
 \end{aligned}$$

Table 7.16 shows the distribution  $P(\text{SoreThroat} | \text{Angina}, \text{Cold})$ .

Angina	Cold	SoreThroat	
		false	true
false	false	1	0
false	true	0.2	0.8
true	false	0.1	0.9
true	true	0.02	0.98

**Table 7.16.** The conditional probability distribution  $P(\text{SoreThroat} | \text{Angina}, \text{Cold})$  with a zero background event probability.

Next, assume the background inhibitor is 0.95 (i.e., the probability that sore throat is caused by the background event (other causes not represented in the model) is 0.05 such that  $q_0 = 0.95$ ). The combined impact of Angina, Cold, and the background event on SoreThroat given is computed as:

$$\begin{aligned}
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{false}, \text{Cold} = \text{false}, \Theta_E) &= 0.95, \\
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{false}, \text{Cold} = \text{true}, \Theta_E) &= 0.95 * 0.2, \\
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{true}, \text{Cold} = \text{false}, \Theta_E) &= 0.95 * 0.1, \\
 P(\text{SoreThroat} = \text{false} | \text{Angina} = \text{true}, \text{Cold} = \text{true}, \Theta_E) &= 0.95 * 0.1 * 0.2.
 \end{aligned}$$

Table 7.17 shows the distribution  $P(\text{SoreThroat} | \text{Angina}, \text{Cold})$ .

Angina	Cold	SoreThroat	
		false	true
false	false	0.95	0.05
false	true	0.19	0.81
true	false	0.095	0.905
true	true	0.019	0.981

**Table 7.17.** The conditional probability distribution  $P(\text{SoreThroat}|\text{Angina}, \text{Cold})$  with a non-zero background event probability.

By exploiting the independence of causal influence between **Cold** and **Angina** the number of parameters to elicit has decreased from four to two. This may seem to be an insignificant reduction. However, if we consider the case where ten different causes of **SoreThroat** are to be represented explicitly in the model, then the number of parameters to elicit is reduced from 1024 to ten.

The benefit of independence of causal influence becomes even more apparent when the effect has a large number of causes as the number of parameters grows linearly with the number of causes. The advantage of independence of causal influence is an exponential decrease in the number of parameters to elicit. The disadvantage of independence of causal influence is that any synergy between causes (with respect to their combined impact on the effect variable) is ignored.

Using independence of causal influence in conjunction with parent divorcing may reduce the complexity of inference exponentially.

Srinivas (1993) discusses a generalization of the Noisy-OR model to non-binary variables. Pradhan et al. (1994) and Diez (1993) have considered in detail the Noisy-MAX model as a generalization of the Noisy-OR model to the case in which each variable is allowed to have a finite discrete state space. In the Noisy-MAX model, the max operator specifies the combination of the cause variables. In the Noisy-MAX model the probability distribution of the effect variable  $E$  given its parent causes can be expressed as:

$$P(E|C_1, \dots, C_n) = \sum_{\max(E_1, \dots, E_n)} \prod_{i=1}^n P(E_i|C_i).$$

One prerequisite for using the Noisy-MAX model is that the variable state spaces are ordered as, for example (**absent**, **mild**, **moderate**, **severe**). In addition, each cause variable must have a *distinguished* (or **absent**) state designating an influence of the cause on the effect variable.

## How to Implement This Technique

The independence of causal influence modeling technique is implemented as follows.

- (1) Let  $\{C_1, \dots, C_n\}$  be the set of causes of effect variable  $E$ .
- (2) Assume the impact of  $C_1, \dots, C_n$  on  $E$  can be modeled as a Noisy-OR model. Hence,  $C_1, \dots, C_n$  and  $E$  are Boolean variables.
- (3) Create one Boolean contribution variable  $E_i$  for each  $C_i \in \{C_1, \dots, C_n\}$ .
- (4) Let each  $E_i$  be a child of  $C_i$  and a parent of  $E$ .
- (5) For each  $C_i$ , define the conditional probability distribution  $P(E_i|C_i)$  such that  $P(E_i = \text{true}|C_i = \text{true})$  is the probability of  $E = \text{true}$  given  $C_i = \text{true}$  and  $C_j = \text{false}$  for  $i \neq j$  and  $P(E_i = \text{false}|C_i = \text{false}) = 1$ .
- (6) Define the conditional probability distribution  $P(E|E_1, \dots, E_n)$  as disjunction (i.e., or).

Once the independence of causal influence modeling technique has been applied, it may be an advantage to use the parent divorcing modeling technique (see Section 7.1.1) to reduce the number of parents of the effect variable.

## 7.2.6 Mixture of Gaussian Distributions

When modeling problem domains with continuous entities a decision on how to represent the continuous entities in a network has to be made. One option is to represent a continuous entity as a discrete variable with states representing intervals for the continuous entity. For instance, we may choose to represent temperature as a discrete variable with three states *low*, *medium* and *high*. In other cases we may choose to approximate the distribution of a continuous entity using the conditional linear Gaussian distribution.

A third option is presented in this section. The third option is to approximate the continuous distribution of a variable using a mixture of Gaussian distributions (MoGs). This option is interesting as it is well known that mixtures of Gaussian distributions can approximate any probability distribution; see Shenoy (2006) who cites Titterton, Smith & Makov (1995).

An MoGs is a sum of Gaussian distributions where each component is weighted by a number between zero and one such that the sum of the weights is one, i.e., the weights are probabilities. Assume  $X$  is a continuous variable with a probability distribution that can be approximated using the MoGs

$$f(x) = \sum_{i=1}^n p_i \cdot \mathcal{N}(\alpha_i, \gamma_i), \quad (7.4)$$

where  $\alpha_i, \gamma_i \in \mathbb{R}$  and  $0 \leq p_i \leq 1$  such that  $\sum_i p_i = 1$  are the mean, variance, and weight of the  $i$ 'th component in the mixture.

To approximate the probability distribution on  $X$  using Equation 7.4, a selector variable  $S$  with  $n$  states is introduced as a parent of  $X$ . The variable  $X$  becomes a continuous variable with a conditional linear Gaussian distribution, see Section 4.1.2. Each state  $s_i$  of  $S$  corresponds to one component  $p_i \cdot \mathcal{N}(\alpha_i, \gamma_i)$  in the mixture. The prior distribution on  $S$  is  $P(S = s_i) = p_i$  while  $X|s_i \sim \mathcal{N}(\alpha_i, \gamma_i)$ . Figure 7.27 illustrates the use of the MoGs modeling technique on the distribution for  $X$ .



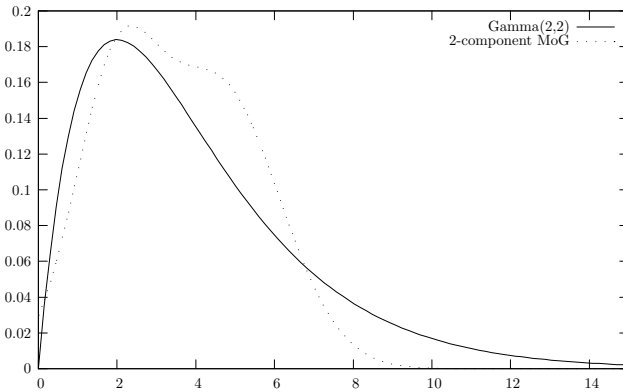
**Fig. 7.27.** Approximation of a continuous distribution using the MoGs modeling technique.

Using MoGs the network becomes either a CLG Bayesian network or a CLQG influence diagram.

*Example 7.14.* A Gamma(2,2) distribution can, for instance, be approximated using a two-component mixture of MoGs such as

$$f(x) = 0.609 \cdot \mathcal{N}(4.57, 2.37) + 0.391 \cdot \mathcal{N}(1.93, 1.12). \quad (7.5)$$

Figure 7.28 shows the result of approximating the Gamma(2,2) distribution with the above two-component mixture of Gaussian distributions.



**Fig. 7.28.** A two-component mixture approximation of the Gamma(2,2) distribution.

The two-component approximation in Equation 7.5 produces a reasonable fit to the Gamma(2,2) distribution. Whether or not the fit is of sufficient quality depends on the problem domain and application.

The MoGs modeling technique introduces a discrete random variable with one state for each component in the mixture. Approximating continuous distributions using the MoGs modeling technique is not necessarily simple and may produce networks where belief updating is computationally intensive.

## How to Implement This Technique

The mixture of Gaussian distributions modeling technique is implemented as follows.

- (1) Let  $X$  be the variable of the probability distribution to approximate.
- (2) Assume the probability distribution of  $X$  can be approximated using the MoGs

$$f(x) = \sum_{i=1}^n p_i \cdot \mathcal{N}(\alpha_i, \gamma_i).$$

- (3) Create a discrete variable  $S$  with  $n$  states.
- (4) Let  $S$  be the parent of  $X$  in the network with  $P(S = s_i) = p_i$ .
- (5) For each state  $s_i$  of  $S$  set  $X|s_i \sim \mathcal{N}(\alpha_i, \gamma_i)$ .

The process of identifying the number of components as well as the parameterization and weight of each component is not trivial.

In this section we have considered the case of approximating the prior distribution of a continuous variable with no parents. Shenoy (2006) presents a methodology for belief updating in hybrid Bayesian networks (i.e., Bayesian networks with both continuous and discrete variables and with no restrictions on the model structure) based on approximating distributions using MoGs. Shenoy (2006) gives examples on how to approximate different types of distributions using MoGs. This includes approximating the distribution of a discrete child of a continuous variable. Poland (1994) has presented an algorithm for identifying MoGs using the EM algorithm (see Section 8.3.1).

## 7.3 Decision Related Techniques

In this section we consider modeling techniques related to the specification of a decision problem as an influence diagram. In particular we consider how to model test decisions, how to exploit missing informational links, how to model variables which may or may not be observed prior to a decision, how to force a decision variable to be in a state corresponding to a hypothesis of maximum probability, and how to enforce constraints on decision options.

### 7.3.1 Test Decisions

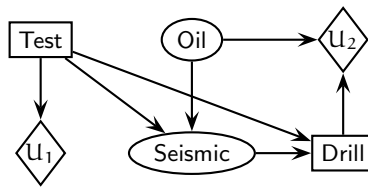
As part of a decision problem, a decision maker may be faced with the option to perform some kind of test. Performing the test produces a test result which is modeled as a random variable with states corresponding to the possible test results in an influence diagram. In addition to the random variable representing the test result, the influence diagram has a decision variable with states representing whether or not the test is performed. If the test is performed, then the result of the test (usually) becomes available to the decision maker.



If the test, on the other hand, is not performed, then no test result becomes available. The influence diagram may also have a utility function associated with the test specifying the cost of the test. Solving the influence diagram will produce a policy for when to perform the test.

The random variable representing the test result may be an informational parent of another decision variable in the influence diagram. If the test result variable is an informational parent of another decision in the influence diagram, then the variable must be observed prior to this decision. This, however, contradicts the fact that the test result is available only when the test is performed. In this section we consider two examples that illustrate different approaches to alleviating this contradiction.

*Example 7.15 (Oil Wildcatter (Raiffa 1968)).* Example 4.5 on page 77 considers an oil wildcatter about to decide whether or not to drill for oil at a specific site. Prior to her decision on whether or not to drill for oil the oil wildcatter has the option to take seismic soundings to better understand the geological structure of the site. The structure of the Oil Wildcatter model (Figure 4.5 on page 77) is repeated in Figure 7.29 for convenience.



**Fig. 7.29.** The test result is only available after a test is performed.

There are two informational links in the graph of Figure 7.29. The link (Test, Drill) from Test to Drill and the link (Seismic, Drill) from Seismic to Drill are both informational links. The former link specifies whether or not the oil wildcatter decided to take seismic soundings prior to the drill decision. On the other hand, the latter link specifies that the value of Seismic is also known when making the drill decision. This cannot, however, be the case when the test is not performed.

We consider two alternative options to correct this problem. Both options consider the specification of the conditional probability distribution  $P(\text{Seismic} | \text{Oil}, \text{Test})$ .

One option is to specify  $P(\text{Seismic} | \text{Oil}, \text{Test} = \text{no})$  as a uniform distribution. The corresponding distribution is shown in Table 7.18. If the oil wildcatter decides not to perform the test, then any observation on Seismic will not effect the belief in Oil (the likelihood potential over Oil induced by the observation on Seismic assigns equal likelihood to all states of Oil due to the uniform distribution).

Test	Oil	Seismic		
		closed	open	diffuse
no	dry	0.1	0.3	0.6
no	wet	0.3	0.4	0.3
no	soaking	0.5	0.4	0.1
yes	dry	1/3	1/3	1/3
yes	wet	1/3	1/3	1/3
yes	soaking	1/3	1/3	1/3

**Table 7.18.** The conditional probability distribution  $P(\text{Seismic}|\text{Test}, \text{Oil})$ .

The other option is to introduce an additional **no result** state in **Seismic**. The distribution  $P(\text{Seismic}|\text{Oil}, \text{Test} = \text{no})$  is specified such that not performing the test instantiates **Seismic** to **no result**. The corresponding distribution is shown in Table 7.19. If the oil wildcatter decides not to perform the test, then **Seismic** is instantiated to **no result**.

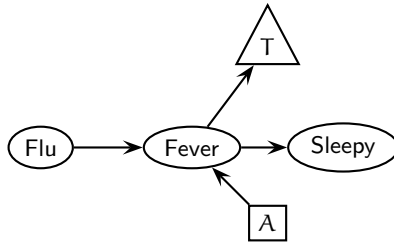
Test	Oil	Seismic			
		closed	open	diffuse	no result
no	dry	0.1	0.3	0.6	0
no	wet	0.3	0.4	0.3	0
no	soaking	0.5	0.4	0.1	0
yes	dry	0	0	0	1
yes	wet	0	0	0	1
yes	soaking	0	0	0	1

**Table 7.19.** The conditional probability distribution  $P(\text{Seismic}|\text{Test}, \text{Oil})$  where **Seismic** has a **no result** state.

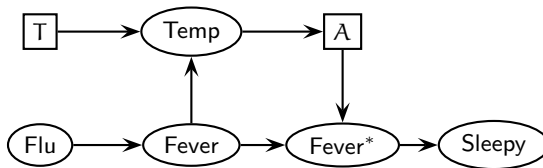
The latter option is semantically more clear than the former option in the sense that it is easily understood that **Seismic** should be instantiated to **no result** when the test is not performed. On the other hand, the latter option increases the complexity of the model by introducing the additional **no result** state in the **Seismic** variable.

*Example 7.16 (Aspirin (Jensen 1996)).* Example 7.12 on page 204 describes a simple model for reasoning about the effect of flu on fever and the effect of fever on sleepiness. Here we consider this example as a decision problem where the decision maker has to decide on whether or not to take an aspirin.

The level of fever may be reduced by taking an aspirin. This is represented by the decision variable **A**. Prior to taking an aspirin there is the option to measure temperature. This option is indicated using the triangular-shaped node with label **T** in Figure 7.30.



**Fig. 7.30.** Prior to deciding on whether or not to take an aspirin, we may measure the temperature.



**Fig. 7.31.** The test for temperature is modeled as a decision value with a random variable as a child specifying the result of the test.

The test option indicated in Figure 7.30 by the triangular-shaped node may be represented using three nodes as indicated in Figure 7.31. The three nodes represent decision variable  $T$  and random variables  $Temp$ , and  $Fever^*$ . The decision variable  $T$  represents whether or not the temperature is measured. The random variable  $Temp$  specifies the temperature measured and the random variable  $Fever^*$  represents the level of fever after taking an aspirin while the random variable  $Fever$  represents the level of fever prior to taking an aspirin.

### How to Implement This Technique

The test decisions modeling technique is implemented as follows.

- (1) Let  $P$  be a discrete random variable representing the phenomenon that may be measured by a test.
- (2) Create a decision variable  $T$  with two states **no test** and **test** corresponding to not performing and performing the test, respectively.
- (3) Create a discrete random variable  $R$  representing the result of the test as a child of  $D$  and  $P$ .
- (4) Let  $R$  have one state for each possible test result and the state **no result** representing the event that the test is not performed, i.e.,  $T = \text{no test}$ .
- (5) Define the conditional probability distribution  $P(R|P, T)$  such that  $P(R = \text{no result}|P, T = \text{no test}) = 1$  and  $P(R|P, T = \text{test})$  encodes the probability of each possible test result given the actual value of phenomenon  $P$ .

Instead of using the state **no result** to specify no test result, a uniform distribution may be used. Furthermore, the modeling technique may be used in combination with the measurement uncertainty modeling technique described in Section 7.2.1.

### 7.3.2 Missing Informational Links

Informational links of an influence diagram define the points at which information is assumed to become available to the decision maker. An informational link  $(X, D)$  from a random variable  $X$  to a decision variable  $D$  specifies that the value of  $X$  is known to the decision maker when the decision corresponding to decision variable  $D$  is made. The informational links of an influence diagram induce a partial order over the random variables relative to the decision variables. The partial order over random variables is important for the solution of an influence diagram. In essence the partial order over random variables induces a constraint on the order in which variables may be eliminated when solving the decision model; see Section 5.2 for details on solving decision models. Thus, correct specification of informational links is imperative.

When the influence diagram has only a single decision, then informational links can be ignored if the influence diagram is solved for each set of evidence. That is, the influence diagram is solved prior to making the decision each time the influence diagram is used. This implies that the optimal strategy is only implicitly available to the decision maker as the optimal decision is determined for each evidence scenario prior to making the decision. This can be particularly useful if the optimal policy for the decision has a large state space.

*Example 7.17.* In Example 7.6 on page 192 we considered the task of monitoring the pregnancy state of a cow. Assume that in addition to the blood and urine tests we have the option to make a scanning of the cow. A scanning of the cow will produce a more accurate estimation of the pregnancy of the cow. The option to scan the cow introduces the variable  $Sc$  with states **false** and **true** as a child of  $Pr$ .

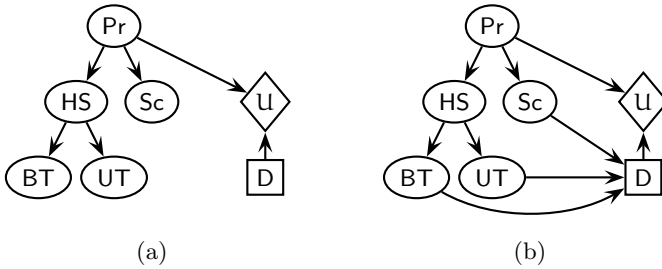
The pregnancy state of the cow is estimated six weeks after the initial insemination of the cow. Based on the observations and the probability distribution of the pregnancy state of the cow, we need to make a decision on whether or not to repeat the insemination of the cow or to wait for another six weeks before estimating the pregnancy state of the cow. This decision introduces the decision variable  $D$  with states **wait** and **repeat**.

The cost of repeating the insemination is 65 no matter the pregnancy state of the cow. If the cow is pregnant, and we wait, it will cost us nothing, but if the cow is not pregnant, and we wait, it will cost us another 30 units plus the eventual repeated insemination (that makes a total of 95 for waiting). A blood test has the cost 1 and a urine test has the cost 2. This defines a utility function over variables  $Pr$  and  $D$ , see Table 7.20.

Pr	D	
false	wait	-95
false	repeat	-65
true	wait	0
true	repeat	-65

**Table 7.20.** The utility function  $U(\text{Pr}, D)$ .

Figure 7.32(a) shows the resulting structure of the model. Notice that there are no informational links in the structure.



**Fig. 7.32.** (a) Informational links are unnecessary in influence diagrams with a single decision. (b) Informational links only clutter up the graph.

Since the structure in Figure 7.32(a) does not contain any informational links, it does not properly reflect the test options available prior to deciding on whether or not to repeat the insemination.

To capture the three test options we may introduce an additional *no test* state in each of the test result variables (BT, UT, and Sc). This would produce the structure shown in Figure 7.32(b).

Alternatively, we may use the fact that the decision problem contains a single decision variable. This allows us to leave out informational links and instantiate the random variables observed prior to the decision as the observations are made. This leaves us with Figure 7.32(a) instead of the more cluttered Figure 7.32(b).

When informational links are included in the influence diagram the solution will identify a decision policy specifying an optimal decision option for each configuration of the parents of the decision. Thus, the influence diagram is solved once and *off-line* in the sense that the influence diagram is solved before the decision maker has to make a decision and before any observations are made. On the other hand, it is necessary to resolve the influence diagram each time the decision maker has to make the decision when informational

links are not included in the network. The solution process identifies an optimal decision option for the specific set of observations made prior to the decision. The influence diagram is solved *on-line* in the sense that the influence diagram is solved when the decision maker has to make the decision and after observations have been made. Solving the influence diagram on-line is often a significantly simpler task than solving it off-line and may be the only option when the influence diagram is complex.

### How to Implement This Technique

The missing informational links modeling technique is implemented as follows.

- (1) Let  $D$  be the decision under consideration.
- (2) Assume observations  $\varepsilon$  have been made prior to making decision  $D$  where  $\text{pa}(D) \subseteq \mathcal{X}(\varepsilon)$ .
- (3) Insert  $\varepsilon$  as evidence and solve the influence diagram.
- (4) The expected utility associated with each state  $d$  of  $D$  is  $\text{EU}(d|\varepsilon)$ , i.e., the expected utility of decision option  $d$  given observations  $\varepsilon$ .

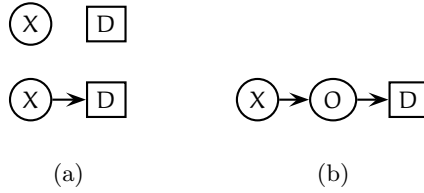
The above steps should be repeated each time observations are made prior to deciding on  $D$ .

#### 7.3.3 Missing Observations

The structure of an influence diagram induces a partial order on the random variables of the model relative to the decision variables of the model. The partial order is induced by the informational links of the graph of the influence diagram. An informational link  $(X, D)$  from a node representing a random variable  $X$  to a node representing a decision variable  $D$  specifies that the value of  $X$  is observed when decision  $D$  is to be made. That is, the value of  $X$  is *always* observed prior to decision  $D$ .

Figure 7.33(a) illustrates a typical dilemma a knowledge engineer may be faced with when representing a decision problem as an influence diagram. In some situations the random variable  $X$  is observed prior to the decision represented as  $D$  and in other situations it is not observed prior to making decision  $D$ . In this section we describe a modeling technique for solving the dilemma where a random variable  $X$  *may or may not* be observed prior to a decision  $D$ . This is a typical and frequently occurring situation when considering decision problems with sensor readings or other similar types of observations, which may, for some reason, be missing or lost.

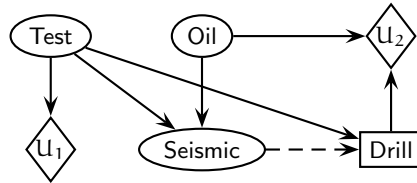
Figure 7.33(b) illustrates the solution to the dilemma. An auxiliary variable  $O$  is introduced as a child of  $X$  and a parent of  $D$ . The random variable  $O$  has the state space of  $X$  extended with one additional state, e.g., named *none*. Each state  $o \in \text{dom}(O)$  corresponding to state  $x \in \text{dom}(X)$  represents an observation of  $X$  to the state  $x$  while the additional state *none* represents the event that  $X$  is not observed. The conditional probability distribution  $P(O|X)$



**Fig. 7.33.** (a) In some situations  $X$  is observed prior to  $D$  while in others it is not. (b) By introducing an additional variable, we capture the situation where an observation on  $X$  may or may not be available.

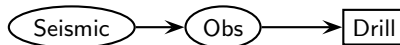
is constructed such that  $P(O = o | X = x) = p$  and  $P(O = \text{none} | X = x) = 1 - p$  where  $p$  specifies the probability that the observation on  $X$  is made when  $X$  is in state  $x$ . The following example illustrates the use of this modeling technique.

*Example 7.18.* In Example 4.5 on page 77 the oil wildcatter has the option to take seismic soundings prior to the drill decision. In this example we will assume that the oil wildcatter is not in full control of the test option. This implies that the test event should be modeled as a random variable. Figure 7.34 shows the resulting structure.



**Fig. 7.34.** The observation on **Seismic** is missing when the test is not performed.

The dashed link from **Seismic** to **Drill** indicates that **Seismic** is only observed when the test is performed. This property can be captured by the approach described above. Figure 7.35 shows the structure which captures the situation where the result of seismic soundings may not be available.



**Fig. 7.35.** This graph captures the situation where the result of seismic soundings may not be available.

The conditional probability distribution of **Obs** is shown in Table 7.21. The variable **Obs** has one state for each state of **Seismic** and one additional state **none** representing the event that no result is available. The table specifies the probability that the result of seismic soundings is available to be 0.9.

Seismic	Obs			
	closed	open	diffuse	none
closed	0.9	0	0	0.1
open	0	0.9	0	0.1
diffuse	0	0	0.9	0.1

**Table 7.21.** The conditional probability distribution  $P(\text{Obs}|\text{Seismic})$ .

The variable **Obs** is always observed. Either it instantiates **Seismic** to the state representing the seismic soundings result or it carries no information on the test result.

### How to Implement This Technique

The missing observations modeling technique is implemented as follows.

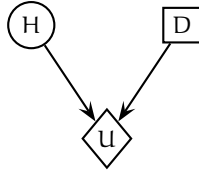
- (1) Let **X** be the discrete random variable that may or may not be observed prior to decision **D**.
- (2) Create a discrete random variable **O** with state space  $\text{dom}(\text{O}) = \text{dom}(\text{X}) \cup \{\text{none}\}$  representing the observation on **X** when it is observed and **none** when it is not.
- (3) Let **X** be the parent of **O** and let **O** be a parent of **D**.
- (4) Define the prior probability distribution  $P(\text{O}|\text{X})$  such that  $P(\text{O} = \text{o}|\text{X} = \text{x}) = p$  and  $P(\text{O} = \text{none}|\text{X} = \text{x}) = 1 - p$  where  $p$  specifies the probability that the observation on **X** is made when **X** is in state **x**.
- (5) Instantiate **O** to the state of **X** when **X** is observed and instantiate **O** to the state **none** when **X** is not observed.

### 7.3.4 Hypothesis of Highest Probability

An influence diagram is useful for solving problems of decision making under uncertainty. The variables of an influence diagram consist of a mixture of random variables and decision variables. The random variables are used for representing uncertainty while the decision variables represent entities under the full control of the decision maker. The state of a random variable may be observable or hidden while the state of a decision variable is under the full control of the decision maker.

As indicated above there is a fundamental difference between random variables and decision variables. Situations exist, however, where it is useful to



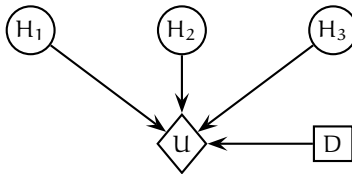


**Fig. 7.36.** Decision  $D$  selects a hypothesis of maximum probability.

have the decision maker select a decision option corresponding to the state of a random variable. In a medical diagnosis situation, for instance, it may be necessary to have the model suggest the most likely diagnosis as the disease with the maximum probability where the presence or absence of diseases are modeled as random variables. Figure 7.36 illustrates a simple modeling technique for representing this situation. Let  $D$  be the discrete decision variable under the full control of the decision maker and let  $H$  be the hypothesis variable such that  $D$  and  $H$  have the same (or equivalent) state spaces, i.e.,  $\text{dom}(D) = \text{dom}(H)$ . The goal is to assign the maximum expected utility to the decision option  $d$  of  $D$  corresponding to the hypothesis  $h$  of  $H$  with maximum probability. This is achieved by adding a utility function  $U$  with domain  $\text{dom}(U) = \{D, H\}$  assigning utilities to configurations of  $H$  and  $D$  as

$$U(h, d) = \begin{cases} 1 & \text{if } h = d \\ 0 & \text{otherwise.} \end{cases}$$

That is, all configurations where the decision variable  $D$  and the hypothesis variable  $H$  are in the *same* state are assigned the value one, while all remaining configurations are assigned the value zero. In effect each state of  $D$  has expected utility corresponding to (a linear transformation of) the probability of the hypothesis. Since influence diagrams are solved by selecting the decision option with maximum expected utility, the optimal decision policy for  $D$  will select a hypothesis with maximum probability.

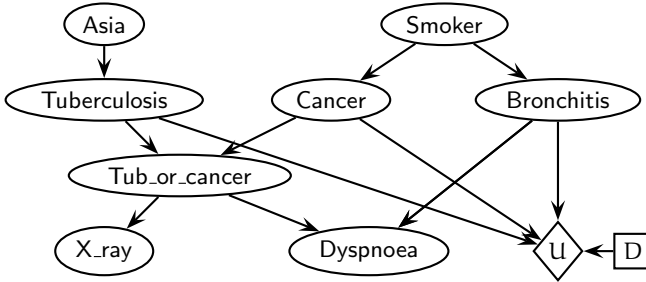


**Fig. 7.37.** Decision  $D$  selects a hypothesis of maximum probability.

In the general case each hypothesis  $h$  may be a configuration over a set of variables such that the utility function has more than one hypothesis variable as parent. Figure 7.37 illustrates this situation.

*Example 7.19.* In the Chest Clinic example (Example 4.2 on page 68) a physician is diagnosing her patients with respect to lung cancer, tuberculosis, and bronchitis based on observations of symptoms and possible causes of the diseases.

Assume the physician would like to select the single diagnosis with highest probability. Figure 7.38 shows the structure of a model where the decision variable  $D$  selects the disease hypothesis with highest probability. The decision variable  $D$  has states **bronchitis**, **cancer**, and **tuberculosis**.



**Fig. 7.38.** Selecting a disease hypothesis with highest probability.

The utility function  $U(T, L, B, D)$  encodes the behavior of the model and it is specified as

$$U(T, L, B, D) = \begin{cases} 1 & \text{if } B = \text{yes}, L = \text{no}, T = \text{no} \text{ and } D = \text{bronchitis} \\ 1 & \text{if } B = \text{no}, L = \text{yes}, T = \text{no} \text{ and } D = \text{cancer} \\ 1 & \text{if } B = \text{no}, L = \text{no}, T = \text{yes} \text{ and } D = \text{tuberculosis} \\ 0 & \text{otherwise.} \end{cases}$$

This model will enforce the expected utility function over  $D$  to assign the hypothesis with the highest probability with the maximum expected utility.

### How to Implement This Technique

The hypothesis of highest probability modeling technique is implemented as follows.

- (1) Let  $H$  be the random variable for which the hypothesis (i.e., state) of highest probability is to be selected.
- (2) Create a decision variable  $D$  with the same state space as  $H$ , i.e., such that  $\text{dom}(D) = \text{dom}(H)$ .
- (3) Create a utility function  $U$  with  $D$  and  $H$  as its parents.

(4) Define the utility function  $U(H, D)$  such that

$$U(h, d) = \begin{cases} 1 & \text{if } h = d \\ 0 & \text{otherwise} \end{cases}$$

where  $h$  and  $d$  are states of  $H$  and  $D$ , respectively.

### 7.3.5 Constraints on Decisions

One of the underlying assumptions of representing and solving a decision making problem with uncertainty using influence diagrams is that the decision maker is in full control of her decision options. It is, however, common that a decision making problem is subject to certain constraints on the decisions (and random) variables. We consider the situation where certain configurations of decision variables are illegal in the sense that such configurations should never be optimal.

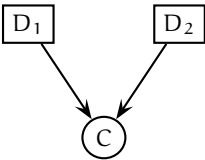
There are two alternatives to enforcing constraints on decision options. The basic idea of the first alternative is to assign an infinitely large negative value to configurations of decision options that are illegal. Since influence diagrams are solved by maximizing the expected utility, decision options with infinitely large negative expected utilities will not be chosen.

It is not possible to specify that a configuration of variables has infinitely large negative expected utility. Instead of using an infinitely large negative value we may use zero (or a very large negative value). This implies that it may be necessary to make a linear utility transformation to avoid zero expected utilities for any configuration which is not illegal. This transformation of the utility function will preserve the optimal policy.

The second alternative is to use an extension of the constraints modeling technique of Section 7.1.4 to the case of influence diagrams. Using constraints we are able to ensure that *illegal* configurations are avoided. Using constraints we assign zero probability to configurations of variables that are illegal. Since influence diagrams are solved by maximizing expected utility we need to make sure that only illegal configurations have expected utility zero and no other configuration has lower or equal expected utility. This can be achieved by a linear transformation of the utility function such that all utilities in the model are positive except for configurations that are illegal.

*Example 7.20.* Assume that two decisions  $D_1$  and  $D_2$  specify two different points in time where the decision maker can choose to sell an old car that needs repair. If both decisions are to keep the car, then a repair cost of is induced. If the car is sold at decision  $D_1$ , then it is not an option to sell the car at decision  $D_2$ .

This implies that options available for the decision maker at decision  $D_2$  are constrained by the decision made at decision  $D_1$ . This property can be encoded as a constraint over  $D_1$  and  $D_2$  as illustrated in Figure 7.39 with the distribution  $P(C|D_1, D_2)$  as specified in Table 7.22.



**Fig. 7.39.** A constraint on configurations of decisions  $D_1$  and  $D_2$ .

D <sub>1</sub>	D <sub>2</sub>	C	
		off	on
keep	keep	0	1
keep	sell	0	1
sell	keep	0	1
sell	sell	1	0

**Table 7.22.** The conditional probability distribution  $P(C|D_1, D_2)$ .

In order to avoid problems related to decision options having zero expected utility due to illegal events, a linear transformation of the utility function can be made. In the example we may add a constant greater than the numerical value of the cost of repairing the car to all utilities. This will force all utilities to be positive and zero expected utility to be assigned to illegal configurations only.

The constraint is enforced by instantiating  $C$  to **on**.

In the example we assume that  $D_1$  and  $D_2$  are temporally ordered in the enclosing model, i.e., decision  $D_1$  is made prior to decision  $D_2$ . This assumption has no impact on the model.

**How to Implement This Technique**

The constraints on decisions modeling technique is implemented as follows (assuming that we use constraints as opposed to large negative utility values to encode the constraint).

- (1) Let  $\{D_1, \dots, D_n\}$  be the set of decisions to be constrained.
- (2) Create a binary constraint node  $C$  with one state **off** representing all illegal configurations and one state **on** representing all legal configurations.
- (3) Add each  $D \in \{D_1, \dots, D_n\}$  as a parent of  $C$ .
- (4) Define the conditional probability distribution  $P(C|D_1, \dots, D_n)$  such that all illegal configurations of  $\{D_1, \dots, D_n\}$  map to the state **off** and all legal configurations of  $\{D_1, \dots, D_n\}$  map to the state **on**.
- (5) Instantiate  $C$  to state **on** enforcing the constraint.

If a linear transformation of the utility function is required, this should be performed subsequently.

## 7.4 Summary

In this chapter we have introduced modeling methods and techniques for adjusting the structure of a probabilistic network, for the specification of conditional probability distributions and for influence diagram models.

The construction of a probabilistic network may be a labor-intensive task to perform. A sequence of steps related to knowledge acquisition and representation is performed in the process of constructing a probabilistic network. The steps include identifying variables, identifying states of variables, identifying and encoding dependence and independence relations among variables as an acyclic, directed graph and eliciting the quantification of the model as required by the structure.

In Chapter 8 we discuss methods for data-driven modeling.

## Exercises

**Exercise 7.1.** Assume that the causal influences of Angina, Cold, and Flu on SoreThroat can be assumed to be independent. Furthermore, assume that there is a *background* event that can cause the throat to be sore.

The probability of a sore throat being caused by other causes is 0.05 whereas the inhibitor probabilities for Angina, Cold, and Flu are 0.3, 0.4, and 0.25, respectively. The prior probabilities for Angina, Cold, and Flu are 0.4, 0.1, and 0.25, respectively.

- (a) Construct a Bayesian network model representing the causal impact on SoreThroat.
- (b) Compute the prior probability of SoreThroat.
- (c) Apply the parent divorcing modeling technique to simplify the model.

**Exercise 7.2.** Consider the Asia network in Figure 7.20 on page 200.

- (a) Perform a sequence of node absorption operations to remove the variables Experts<sub>1</sub> and Experts<sub>2</sub>.
- (b) Assume bronchitis can be cured by taking a certain type of medicine. Extend the network accordingly.

**Exercise 7.3.** Consider the Naive Bayes network for classifying mushrooms in Figure 7.15 on page 195. Assume no odor is perfectly observed, whereas almond is mistakenly observed as spicy in 10% of the cases while spicy is mistakenly observed as almond in 5% of the cases. Extend the network accordingly.

**Exercise 7.4.** Consider the Asia network in Figure 4.2 on page 69, see Example 4.2 on page 68.

- (a) Perform a node absorption operation to remove the variable Tub\_or\_cancer.
- (b) Apply the parent divorcing technique on the resulting network.

**Exercise 7.5.** Assume appendicitis may cause fever, pain, or both. If a patient has appendicitis, then the patient will have an increased white blood cells count. When a patient potentially has appendicitis, the physician may choose to carry out surgery right away or wait for a blood test result. Fever and pain are observed.

The prevalence of appendicitis is 0.15. The true positive rates are 0.98, 0.95, and 0.99 for fever, pain, and white\_cells\_count, respectively. The true negative rates are 0.5, 0.4, and 0.95 for fever, pain, and white\_cells\_count, respectively. The utilities of operating are shown in Table 7.23.

	$\neg$ surgery	surgery
$\neg$ appendicitis	5	-5
appendicitis	-10	10

**Table 7.23.** The utility function  $U(\text{Surgery}, \text{Appendicitis})$ .

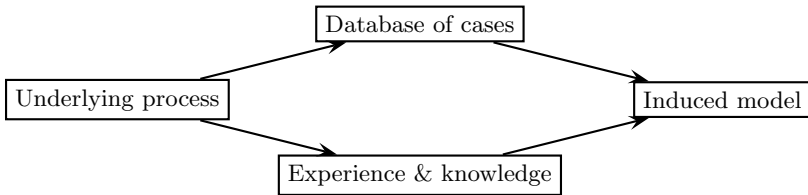
- Build a model for the diagnosis problem.
- Compute the maximum expected utility of the scenario where the physician does not wait for the blood test result.
- Compute the maximum expected utility of the scenario where the physician waits for the blood test result.
- Prior to deciding on whether or not to carry out surgery the physician has the option to carry out a test for the white blood cell count.

Extend the model to include a representation of the test decision.

## Data-Driven Modeling

In this chapter we introduce data-driven modeling as the task of inducing a Bayesian network by fusion of (observed) data and domain expert knowledge.

The data-driven modeling is illustrated in Figure 8.1. The assumption is that some underlying process has generated a database of observed cases as well as domain expert experience and knowledge. The task of data-driven modeling is to fuse these information sources in order to induce a representative model of the underlying process. If the model is a good approximation of the underlying process, then it can be used to answer questions about properties of the underlying process.



**Fig. 8.1.** We assume the underlying process generates a database of cases as well as experience and knowledge that can be fused for learning a model of the process.

In this book we consider the use of Bayesian networks to model the underlying process. The process of inducing a Bayesian network from a database of cases and expert knowledge consists of two main steps. The first step is to induce the structure of the model, i.e., the DAG, while the second step is to estimate the parameters of the model as defined by the structure. In this book we consider only discrete Bayesian networks. Thus, the task of data-driven modeling is to construct a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  from the available information sources. In general, the problem of inducing the structure of a

Bayesian network is NP-complete (Chickering 1996). Thus, heuristic methods are appropriate.

Section 8.1 gives some background on data-driven modeling and presents a set of assumptions underlying the presented approach to data-driven modeling. Section 8.2 considers structure learning of Bayesian networks. A number of different algorithms for structure learning are considered. We consider the PC, PC\*, and NPC algorithms. These algorithms are all constraint-based algorithms. In Section 8.3 we consider the Expectation-Maximization algorithm for parameter estimation. In addition to the two main steps of data-driven modeling there is the step of sequential parameter learning. Structure learning and parameter estimation are performed during the model construction phase whereas sequential parameter learning is performed during model usage. In Section 8.4 we consider sequential parameter learning, which is the task of adjusting parameters of the model as the model is used, i.e., as new cases occur.

Parts of this chapter have appeared in Madsen et al. (2005).

## 8.1 The Task and Basic Assumptions

Data-driven modeling is the task of identifying a Bayesian network model from a source of data. We assume the underlying process follows a probability distribution  $P_0$  (referred to as *the underlying probability distribution of the process*). That is, we assume the data source can be adequately represented by sampling from  $P_0$ . The goal of data-driven modeling is to identify a model representation of  $P_0$ .

To simplify the task, the probability distribution  $P_0$  is assumed to be a *DAG-faithful* probability distribution with underlying DAG  $\mathcal{G}_0$ . That is, we assume that the distribution  $P_0$  can be represented as a Bayesian network (if  $P_0$  is not DAG-faithful, a Bayesian network may still be an excellent approximation).

The *faithfulness assumption* (also known as the *stability* assumption) says that the distribution  $P$  induced by  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  satisfies no independence relations beyond those implied by the structure of  $\mathcal{G}$  (Spirtes, Glymour & Scheines 2000, Pearl 2000). A Bayesian network is faithful if and only if for every d-connection there is a corresponding conditional dependence, i.e.,

$$X \not\perp_{\mathcal{G}} Y \Rightarrow X \not\perp_{\mathcal{P}} Y | Z.$$

We assume the underlying probability distribution  $P_0$  to be DAG-faithful with DAG  $\mathcal{G}_0$ .

The database of cases generated by the underlying and unknown process (i.e., the data source for learning) is denoted  $\mathcal{D} = \{\mathbf{c}^1, \dots, \mathbf{c}^N\}$  where  $N$  is the number of cases in the database. We assume  $\mathcal{D}$  consists of independent and identically distributed data cases drawn at random from the probability



distribution  $P_0$ , i.e., we assume cases are drawn at random and independently from the same probability distribution  $P_0$ .

Each case  $\mathbf{c}^i = \{x_1^i, \dots, x_n^i\}$  in  $\mathcal{D}$  specifies an assignment of a value  $x_j^i$  to each variable  $X_j \in \mathcal{X}$ . Some values in  $\mathcal{D}$  may be missing, but missing values are assumed to be missing at random (MAR) or missing completely at random (MCAR), i.e., the missing data mechanism is uninformative and can be ignored (Cowell et al. 1999). A variable never observed is called a *hidden* or a *latent* variable.

*Example 8.1.* Table 8.1 shows a database of  $N$  cases  $\mathcal{D} = \{\mathbf{c}^1, \dots, \mathbf{c}^N\}$  over  $n$  variables  $\mathcal{X} = \{X_1, \dots, X_n\}$ .

	$X_1$	$X_2$	...	$X_n$
$\mathbf{c}^1$	blue	yes	...	low
$\mathbf{c}^2$	green	no	...	low
$\mathbf{c}^3$	red	N/A	...	high
...	...	...	...	...

**Table 8.1.** A database of cases.

In case  $\mathbf{c}^2$ , for instance, variable  $X_2$  is observed to have value no, i.e.,  $x_2^2 = \text{no}$ , while its value is missing in case  $\mathbf{c}^3$  (missing values are indicated using N/A).

We consider learning a Bayesian network as the task of identifying a DAG structure  $\mathcal{G}$  and a set of conditional probability distributions  $\mathcal{P}$  with parameters  $\Theta$  on the basis of  $\mathcal{D} = \{\mathbf{c}^1, \dots, \mathbf{c}^N\}$  and possibly some domain expert background knowledge.

## 8.2 Structure Learning From Data

Structure learning from data is the task of inducing the structure, i.e., the graph, of a Bayesian network from a source of data. There exists different classes of algorithms for learning the structure of a Bayesian network such as search-and-score algorithms and constraint-based algorithms as well as combinations of the two. We consider structure learning algorithms based on the constraint-based approach (Wermuth & Lauritzen 1983, Verma & Pearl 1992, Spirtes et al. 2000).

In the constraint-based approach, the DAG  $\mathcal{G}$  of a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  is considered as an encoding of a set of (conditional) dependence and independence relations (CIDRs)  $\mathcal{M}_{\mathcal{G}}$ , which can be read off  $\mathcal{G}$  using the d-separation criterion (Lauritzen et al. 1990b, Geiger, Verma & Pearl 1990). Structure learning is then the task of identifying a DAG structure that (best)

encodes a set of CIDs. The set of CIDs may, for instance, be derived from the data source by statistical tests. Based on  $\mathcal{D}$  alone, we can at most hope to identify an equivalence class of graphs encoding the CIDs of the generating distribution  $P_0$ .

A constraint-based structure learning algorithm proceeds by determining the validity of independence relations of the form  $I(X, Y | S_{XY})$  (i.e.,  $X$  is independent of  $Y$  given subset  $S_{XY}$  where  $X, Y \in \mathcal{X}$  and  $S_{XY} \subseteq \mathcal{X}$ ). The structure learning algorithm will work with any information source able to provide such information. We will consider the case where the validity of independence relations is determined by statistical hypothesis tests of independence based on a database of cases.

Applying Occam's Razor (the law of parsimony), see Section 6.6, to the problem of learning the structure of a Bayesian network from a database of cases suggests that the simplest model of a set of competing models is preferable. Why should we adhere to Occam's Razor principle, i.e., adhere to one specific selection bias? One argument is that we want models that generalize correctly with respect to subsequent data and it is unlikely that we by coincidence will find a simple model which fits the data as well as a very complex model.

Learning the structure of a sparse graph is computationally less involved than learning the structure of a dense graph where the number of edges is used as a measure of the density of the graph. Inducing a graph from a sample of cases that require the induced graph to be dense is computationally more expensive than inducing a graph from a sample of cases that require the induced graph to be sparse. In addition, domains that require the induced graph to be dense may be difficult to represent as a Bayesian network as inducing the graph is computationally expensive, representing a dense graph requires a lot of storage, and inference in dense graphs may be intractable.

The size of the space of possible DAGs grows super-exponentially with the number of vertices in the graph. Robinson (1977) gives the following recursive formula for calculating the number  $f(n)$  of DAGs on  $n$  vertices:

$$f(n) = \sum_{i=1}^n (-1)^{i+1} \frac{n!}{(n-i)!i!} 2^{i(n-1)} f(n-i).$$

For example,  $f(10) \approx 4.2 \cdot 10^{18}$ .

### 8.2.1 Basic Assumptions

Under the conditions listed below, the structure learning algorithm considered will discover a DAG structure equivalent to the DAG structure of  $P_0$  (Spirtes et al. 2000)

- The independence relationships have a perfect representation as a DAG. This is the *DAG faithfulness assumption*.

- The database consists of a set of independent and identically distributed cases.
- The database of cases is infinitely large.
- No hidden (latent) variables are involved.
- The statistical tests have no error.

### 8.2.2 Equivalent Models

Two DAGs representing the same set of CIDRs are equivalent in the sense that they can capture the same set of probability distributions. That is, two models  $M_1$  and  $M_2$  are statistically equivalent if and only if they contain the same set of variables and joint samples over them provide no statistical grounds for preferring one over the other.

The equivalence class of a DAG  $\mathcal{G}$  is the set of DAGs with the same set of d-separation relations as  $\mathcal{G}$ . A *PDAG* — an *acyclic, partially directed graph*, i.e., an acyclic graph with some edges undirected (also known as a *pattern* or *essential graph*) — can be used to represent the equivalence class of a set of DAG structures, i.e., a maximal set of DAGs with the same set of d-separation relations (Pearl 2000).

Any two models  $M_1$  and  $M_2$  over the same set of variables, whose graphs  $\mathcal{G}_1$  and  $\mathcal{G}_2$ , respectively, have the same *skeleton*  $\mathcal{G}_S$  (i.e., undirected graph obtained by replacing directed edges with undirected edges) and the same v-structures are *equivalent*. That is, two DAGs  $\mathcal{G}_1$  and  $\mathcal{G}_2$  are equivalent if they have the same skeleton and the same set of uncovered *colliders* (i.e.,  $X \rightarrow Y \leftarrow Z$ -structures where  $X$  and  $Z$  are not connected by a link also known as *v-structures*) (Pearl 2000).

*Example 8.2.* The models  $A \rightarrow B \rightarrow C$  and  $A \leftarrow B \leftarrow C$  and  $A \leftarrow B \rightarrow C$  are equivalent, as they share the skeleton  $A - B - C$  and have no v-structures.

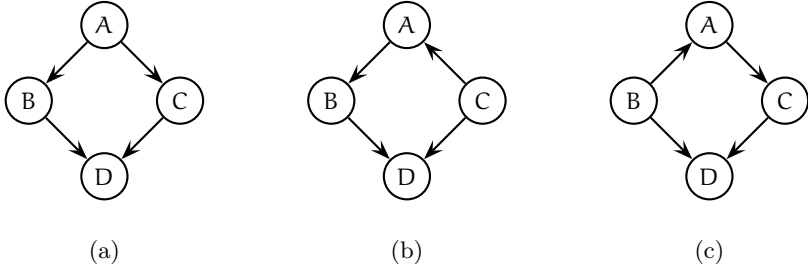
Hence, based on data alone we cannot distinguish  $A \rightarrow B \rightarrow C$  and  $A \leftarrow B \leftarrow C$  and  $A \leftarrow B \rightarrow C$ . These models can, however, be distinguished from  $A \rightarrow B \leftarrow C$ .

An *equivalence class* is a maximal set of DAGs with the same set of independence properties.

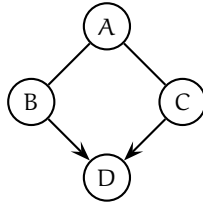
*Example 8.3.* The three DAGs in Figure 8.2 all represent the same set of conditional independence and dependence relations.

Figure 8.3 shows the equivalence class of the three equivalent DAGs of Figure 8.2.

If structure is identified from data, then two DAGs  $\mathcal{G}_i$  and  $\mathcal{G}_j$  from the same equivalence class cannot be distinguished. Based on data alone, we can at most hope to identify a PDAG representing the equivalence class of the generating distribution  $P_0$ .



**Fig. 8.2.** Three equivalent DAGs.



**Fig. 8.3.** The equivalence class of the DAGs in Figure 8.2.

### 8.2.3 Statistical Hypothesis Tests

A set of CIDRs may be generated by statistical tests on the database of cases. In each test, the hypothesis tested is that of independence between a pair of variables.

Let  $X$  and  $Y$  be a pair of variables for which we would like to determine dependence by statistical hypothesis testing. First we test for marginal independence and subsequently we test for conditional independence given subsets of other variables. In the case of marginal independence testing between  $X$  and  $Y$ , the hypothesis to be tested is

$$\begin{aligned} H_0 : P(X, Y) &= P(X)P(Y), \quad \text{i.e., } X \perp\!\!\!\perp_P Y \\ H_1 : P(X, Y) &\neq P(X)P(Y). \end{aligned}$$

Hence, the null hypothesis  $H_0$  is  $X \perp\!\!\!\perp_P Y$  while the alternative hypothesis  $H_1$  is  $X \not\perp\!\!\!\perp_P Y$ .

In order to test the hypothesis we may use the likelihood  $G^2$  test statistic. Under the null hypothesis  $H_0$  the likelihood  $G^2$  test statistic has an asymptotic  $\chi^2$  distribution with the appropriate *degrees of freedom* denoted  $df$ . The likelihood  $G^2$  test statistic is computed as

$$G^2 = 2 \sum_{x,y} N_{xy} \log \left( \frac{N_{xy}}{\mathbb{E}_{xy}} \right),$$

where  $\mathbb{E}_{x,y} = \frac{N_x N_y}{N}$  and  $N_{xy}$  specifies the number of cases in  $\mathcal{D}$  where  $X = x$  and  $Y = y$ .

In the case of conditional independence testing between  $X$  and  $Y$  given a subset  $S_{XY}$ , the hypothesis to be tested is

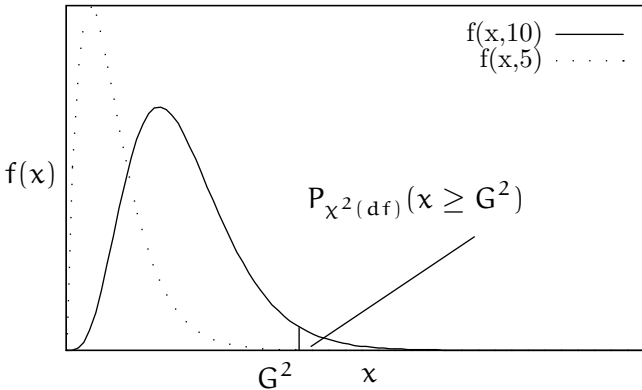
$$\begin{aligned} H_0 : P(X, Y | S_{XY}) &= P(X | S_{XY}) P(Y | S_{XY}), \quad \text{i.e., } X \perp\!\!\!\perp_P Y | S_{XY} \\ H_1 : P(X, Y | S_{XY}) &\neq P(X | S_{XY}) P(Y | S_{XY}). \end{aligned}$$

The null hypothesis  $H_0$  is  $X \perp\!\!\!\perp_P Y | S_{XY}$  while the alternative hypothesis  $H_1$  is  $X \not\perp\!\!\!\perp_P Y | S_{XY}$ . In the case of conditional independence testing, the likelihood  $G^2$  test statistic is computed as

$$G^2 = 2 \sum_{x,y,z} N_{xyz} \log \left( \frac{N_{xyz}}{\mathbb{E}_{xyz}} \right),$$

where  $\mathbb{E}_{xyz} = \frac{N_{xz} N_{yz}}{N_z}$  and  $z$  is a configuration of  $S_{XY}$ .

If the test statistic  $G^2$  is sufficiently small, i.e.,  $G^2 < c$ , then the null hypothesis  $H_0$  is not rejected. Since the value of  $c$  is unknown the probability distribution of  $G^2$  under  $H_0$  and a significance level  $\alpha$  are used. The significance level  $\alpha$  is the probability of rejecting a true hypothesis and is typically set to 0.05 (or 0.01 or 0.001). Not rejecting a hypothesis does not imply that data support independence. A hypothesis is not rejected when there is no evidence in the data against the hypothesis.



**Fig. 8.4.** The  $\chi^2$  density function for different degrees of freedom.

Under the null hypothesis  $H_0$  (i.e., (conditional) independence of  $X$  and  $Y$ ) the likelihood  $G^2$  test statistic has, as mentioned above, an asymptotic  $\chi^2$  distribution with an appropriate number of degrees of freedom denoted  $df$ . The value of  $df$  is defined as

$$\text{df} = (\|X\| - 1)(\|Y\| - 1) \prod_{Z \in S_{XY}} \|Z\|,$$

where  $\|X\|$ ,  $\|Y\|$ , and  $\|Z\|$  are the number of distinct values of  $X$ ,  $Y$ , and  $Z$ , respectively, in  $\mathcal{D}$ .

If the tail probability of the  $\chi^2$  distribution at  $G^2$  is less than  $\alpha$ , then  $H_0$  is rejected. Otherwise it is not rejected. Thus, the hypothesis  $H_0$  is rejected in favor of the alternative hypothesis  $H_1$  when  $P_{\chi^2(\text{df})}(x \geq G^2) < \alpha$ , see Figure 8.4 for an illustration.

In the figure  $f(x, 5)$  and  $f(x, 10)$  are  $\chi^2$  density functions with five and ten degrees of freedom, respectively. The solid line specifies the density function with ten degrees of freedom while  $G^2$  specifies the value of the likelihood  $G^2$  test statistic. The tail of the distribution  $P_{\chi^2(\text{df})}(x \geq G^2)$  is the area indicated in the figure and is often referred to as the p-value. If the tail is less than the significance level, then the independence hypothesis is rejected. It is clear from the figure that it is important to use the correct value of  $\text{df}$  when considering the tail probability of the distribution.

*Example 8.4.* Consider the statistical test for (marginal) independence between a pair of variables  $X$  and  $Y$  with states  $n$  and  $y$  given the sufficient statistics shown in Table 8.2.

X	Y		
	n	y	
n	12	1	13
y	84	3	87
	96	4	100

**Table 8.2.** Sufficient statistics for testing marginal independence of  $X$  and  $Y$ .

The hypothesis to be tested is  $H_0 : X \perp\!\!\!\perp_P Y$  under the distribution induced by the sufficient statistics. Computing the test statistic  $G^2$  proceeds as

$$\begin{aligned}
 G^2 &= 2 \sum_{x,y} N_{xy} \log \left( \frac{N_{xy}}{\mathbb{E}_{xy}} \right) \\
 &= 2 \left( 12 \log \left( \frac{12}{\frac{13*96}{100}} \right) + 1 \log \left( \frac{1}{\frac{13*4}{100}} \right) + 84 \log \left( \frac{84}{\frac{87*96}{100}} \right) + \right. \\
 &\quad \left. 3 \log \left( \frac{3}{\frac{87*4}{100}} \right) \right) \\
 &\approx 0.2194.
 \end{aligned}$$

Since  $G^2 \sim \chi^2(1)$  under  $H_0$  we obtain a p-value of 0.64 (i.e.,  $P_{H_0}(X \geq G^2) = 0.64$ ). At a significance level  $\alpha = 0.01$  we cannot reject the hypothesis  $H_0$ . Hence,  $X$  and  $Y$  are assumed to be independent.

The value of  $df$  is computed as the sum of  $(\|X\| - 1)(\|Y\| - 1)$  over all configurations of  $S_{XY}$  correcting for marginal zero counts (i.e.,  $N_x = 0$  or  $N_y = 0$ ). The value of  $\|X\|$  ( $\|Y\|$ ) is decreased by one for each marginal count equal to zero.

It is common to perform tests  $X \perp\!\!\!\perp Y | S_{XY}$  for  $|S_{XY}| = 0, 1, 2, 3$  as the tests become unreliable (for finite data sets) when the size of  $S_{XY}$  exceeds three as the number of counts  $N_{xyz}$  become too small.

If we *reject*  $H_0$  when it is *true* we incur a *Type I error*. On the other hand, if we *do not reject*  $H_0$  when it is *false* we incur a *Type II error*. In the constraint-based approach to structure learning the relative frequency of Type I and Type II errors can (to some extent) be controlled by varying the significance level used in the statistical tests for conditional independence. The lower the significance level the lower the probability of incurring a Type I error.

## 8.2.4 Structure Constraints

Prior to the testing phase, background knowledge of domain experts in the form of constraints on the structure of the DAG can be specified. It is possible to specify the presence and absence of edges, the orientation of edges, and a combination.

If the background knowledge is assumed to be consistent with the underlying DAG  $\mathcal{G}_0$  of the generating distribution  $P_0$ , then it is not necessary to test the validity of the background knowledge. Hence, specifying background knowledge may reduce the number of statistical tests. Unfortunately, this may, in practice, produce unwanted behavior of the edge-orientation algorithm (as described later). This implies that background knowledge should often be used with caution.

## 8.2.5 PC Algorithm

The PC algorithm (Spirtes & Glymour 1991, Spirtes et al. 2000) (which is similar to the IC algorithm (Verma & Pearl 1992, Pearl 2000)) is a constraint-based algorithm for learning the structure of a Bayesian network. The main steps of the PC algorithm are

- (1) Test for (conditional) independence between each pair of variables represented in  $\mathcal{D}$  to derive  $\mathcal{M}_{\mathcal{D}}$ , the set of CIDs.
- (2) Identify the skeleton of the graph induced by  $\mathcal{M}_{\mathcal{D}}$ .
- (3) Identify colliders.
- (4) Identify derived directions.

The PC algorithm produces a PDAG representing an equivalence class. Each step of the PC algorithm is described in the following sections where the task is to identify a graph  $\mathcal{G}$  representing the independence model of the underlying process generating the database of cases.

### Step (1): Test for (Conditional) Independence

We try to determine the validity of the conditional independence statement  $X \perp\!\!\!\perp Y | S_{XY}$  by a statistical hypothesis test as explained in Section 8.2.3.

The independence hypothesis is tested for conditioning sets  $S_{XY}$  of cardinality 0, 1, 2, 3 in that order. If the hypothesis  $X \perp\!\!\!\perp Y | S_{XY}$  cannot be rejected based on some preselected significance level  $\alpha$ , then the search for an independence relation between  $X$  and  $Y$  is terminated.

*Example 8.5.* Assume  $\mathcal{D}$  is a database of cases generated from the Burglary or Earthquake network in Figure 5.5 on page 115. If the sample is sufficiently large, the conditional independence tests will generate the set  $\mathcal{M}_{\mathcal{D}} = \mathcal{M}_{\perp} \cup \mathcal{M}_{\not\perp}$  of CDIRs where

$$\mathcal{M}_{\perp} = \{B \perp\!\!\!\perp E, B \perp\!\!\!\perp R, B \perp\!\!\!\perp W | A, A \perp\!\!\!\perp R | E, E \perp\!\!\!\perp W | A, R \perp\!\!\!\perp W | A\} \quad (8.1)$$

$$\begin{aligned} \mathcal{M}_{\not\perp} = \{ & B \not\perp\!\!\!\perp A, B \not\perp\!\!\!\perp A | \{E\}, B \not\perp\!\!\!\perp A | \{R\}, B \not\perp\!\!\!\perp A | \{W\}, B \not\perp\!\!\!\perp A | \{E, R\}, \\ & B \not\perp\!\!\!\perp A | \{E, W\}, B \not\perp\!\!\!\perp A | \{R, W\}, B \not\perp\!\!\!\perp A | \{E, R, W\}, A \not\perp\!\!\!\perp E, \dots, \\ & A \not\perp\!\!\!\perp W, \dots, E \not\perp\!\!\!\perp R, \dots\}. \end{aligned} \quad (8.2)$$

We will continue this example in the following subsections describing the steps of the PC algorithm.

### Step (2): Identify the Skeleton

The *skeleton* of an acyclic, directed or partially directed graph  $\mathcal{G}$  is the undirected graph  $\mathcal{G}'$  obtained from  $\mathcal{G}$  by removing the direction on all directed edges. The skeleton of the graph induced from  $\mathcal{M}_{\mathcal{D}}$  is constructed from the conditional dependence and independence statements of  $\mathcal{M}_{\mathcal{D}}$  generated by the statistical test in Step (1) of the PC algorithm.

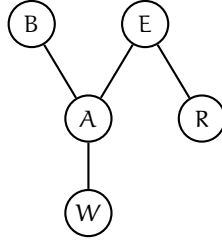
For each pair of variables  $X$  and  $Y$  where no independence statements  $X \perp\!\!\!\perp Y | S_{XY}$  exist, the undirected edge  $(X, Y)$  is created in the skeleton.

*Example 8.6 (Example 8.5 continued).* From  $\mathcal{M}_{\mathcal{D}}$  the skeleton of  $\mathcal{G}$  is generated. The skeleton of  $\mathcal{G}$  generated from  $\mathcal{M}_{\mathcal{D}}$  is shown in Figure 8.5.

Comparing the skeleton of Figure 8.5 with the skeleton of the graph of Figure 5.5 on page 115 we see a perfect match.

In addition, it is obvious that the graph of Figure 8.5 is a more intuitive and compact representation of the dependence and independence model than that of Equation 8.1 and Equation 8.2.



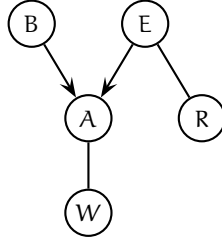


**Fig. 8.5.** Skeleton representing the CDIRs  $\mathcal{M}_{\mathcal{D}}$  of Equation 8.1 and Equation 8.2.

### Step (3): Identify Colliders

Once the skeleton has been identified, colliders in the skeleton are identified. Based on the skeleton, we search for subsets of variables  $\{X, Y, Z\}$  such that  $X$  and  $Y$  are neighbors,  $Z$  and  $Y$  are neighbors while  $X$  and  $Z$  are not neighbors. For each such subset a collider  $X \rightarrow Y \leftarrow Z$  is created when  $Y \notin S_{XZ}$  for any  $S_{XZ}$  satisfying  $X \perp\!\!\!\perp Z | S_{XZ}$  in  $\mathcal{M}_{\mathcal{D}}$ .

*Example 8.7 (Example 8.6 continued).* From the skeleton  $\mathcal{G}_S = (V_S, E_S)$  (see Figure 8.5) and  $\mathcal{M}_{\mathcal{D}}$  (see Equation 8.1 and Equation 8.2) a single collider  $B \rightarrow A \leftarrow E$  is identified, see Figure 8.6. This collider is identified as  $(B, A), (E, A) \in E_S$ ,  $(B, E) \notin E_S$ , and  $A \notin S_{BE}$  for any  $B \perp\!\!\!\perp E | S_{BE}$ .



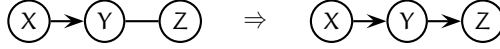
**Fig. 8.6.** Colliders identified from  $\mathcal{M}_{\mathcal{D}}$  and the skeleton of Figure 8.5.

Notice that the collider  $B \rightarrow A \leftarrow W$  is not identified as  $A \in S_{BW}$  for  $B \perp\!\!\!\perp W | S_{BW}$  where  $S_{BW} = \{A\}$ . A similar argument holds for the potential collider  $E \rightarrow A \leftarrow W$ .

### Step (4): Identify Derived Directions

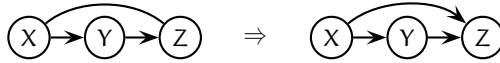
After identifying the skeleton and the colliders of  $\mathcal{G}$ , derived directions are identified. The direction of an edge is said to be *derived* when it is a logical

consequence of (the lack of) previous actions (i.e., since the edge was not directed in a previous step and it should have been in order to have a certain direction, then the edge must be directed in the opposite direction).



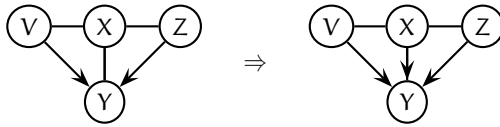
**Fig. 8.7.** Rule  $\mathcal{R}_1$  for identifying derived directions.

Starting with any PDAG including all valid colliders, a maximally directed PDAG can be obtained following four necessary and sufficient rules (Verma & Pearl 1992, Meek 1995). That is, by repeated application of these four rules all edges common to the equivalence class of  $\mathcal{G}$  are identified. The four rules  $\mathcal{R}_1$  to  $\mathcal{R}_4$  are illustrated in Figure 8.7 to Figure 8.10.



**Fig. 8.8.** Rule  $\mathcal{R}_2$  for identifying derived directions.

Rules  $\mathcal{R}_1$  to  $\mathcal{R}_4$  direct edges under the assumption that  $\mathcal{G}$  is a valid DAG, i.e., they ensure that no directed cycle is created in the graph and no additional colliders are created.

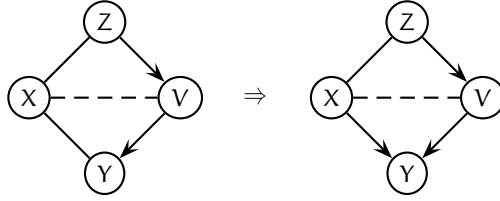


**Fig. 8.9.** Rule  $\mathcal{R}_3$  for identifying derived directions.

Rule  $\mathcal{R}_1$  as illustrated in Figure 8.7 follows from the fact that the collider  $X \rightarrow Y \leftarrow Z$  was not identified as a valid collider. Since the edge between  $Y$  and  $Z$  is not part of the aforementioned collider, it must be directed from  $Y$  to  $Z$ .

Rule  $\mathcal{R}_2$  as illustrated in Figure 8.8 follows from the fact that directing the edge between  $X$  and  $Z$  from  $Z$  to  $X$  will induce a directed cycle in the graph. Thus, the edge must be directed from  $X$  to  $Z$ .

Rule  $\mathcal{R}_3$  as illustrated in Figure 8.9 follows from the fact that directing the edge between  $X$  and  $Y$  from  $Y$  to  $X$  will inevitable produce an additional



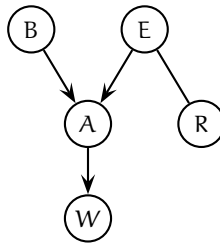
**Fig. 8.10.** Rule  $\mathcal{R}_4$  for identifying derived directions. (The dashed line between X and V indicates that X and V are adjacent, i.e., connected by an edge.)

collider  $V \rightarrow X \leftarrow Z$  or a directed cycle. Hence, the edge must be directed from X to Y.

Rule  $\mathcal{R}_4$  as illustrated in Figure 8.10 follows from the fact that directing the edge between X and Y from Y to X will inevitably produce an additional collider  $Y \rightarrow X \leftarrow Z$  or a directed cycle. Hence, the edge must be directed from X to Y. The dashed lines used to illustrate the fourth rule indicate that X and V are connected by an edge (either directed or not).

The fourth rule is not necessary if the orientation of the initial PDAG is limited to containing colliders only. The initial PDAG may contain non-colliders when expert knowledge on edge directions are included in the graph.

*Example 8.8 (Example 8.7 continued).* As neither the collider  $B \rightarrow A \leftarrow W$  nor the collider  $E \rightarrow A \leftarrow W$  were identified as a collider of  $\mathcal{G}$ , the edge between A and W must be directed from A to W. This is an application of rule  $\mathcal{R}_1$ .



**Fig. 8.11.** Derived directions identified from the skeleton and the colliders identified in Example 8.7.

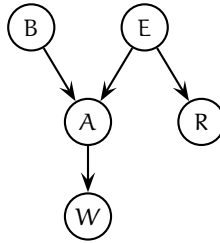
Figure 8.11 shows the equivalence class of  $\mathcal{M}_{\mathcal{D}}$ . The equivalence class contains two DAGs differing only with respect to the orientation of the edge between E and R.

The four rules  $\mathcal{R}_1$  to  $\mathcal{R}_4$  are necessary and sufficient for achieving maximal orientation (up to equivalence) of the PDAG returned by the PC algorithm.

We use these four rules repeatedly until no edge can be given an orientation. Notice that the result of closing edge directions under rules  $\mathcal{R}_1$  to  $\mathcal{R}_4$  is not necessarily a DAG. If the graph is not a DAG, then expert knowledge may be appropriate in order to direct an edge. Once an edge has been directed by use of expert knowledge derived directions should be identified. This process may be repeated until a DAG structure is obtained. Experience shows that most edges are directed using  $\mathcal{R}_1$ , and that  $\mathcal{R}_3$  is only rarely used.

Since the goal of structure learning is to induce a DAG structure over the variables in the data, a decision has to be made on how to handle directed cycles and additional colliders induced by rules  $\mathcal{R}_1$  to  $\mathcal{R}_4$ . In a practical implementation of the algorithm as part of a tool, we suggest to give the user a warning and to enforce the constraint that the induced graph must be acyclic with the possible implication that edges may be reversed after the application of a rule in order to enforce acyclicity.

*Example 8.9 (Example 8.8 continued).* There are two possible completions of the PDAG shown in Figure 8.11 into a DAG. Either the edge between E and R is directed from E to R or vice versa. The two DAGs induce the same set of CDIRs.



**Fig. 8.12.** The result of structure learning.

Since, based on data alone, we cannot determine the direction of the edge between E and R the direction can either be selected at random or we can exploit expert knowledge, if available. From our knowledge of the problem domain and the underlying process, we may argue that if there is an edge between E and R, then it should be directed from E to R. An earthquake may cause a report on the radio reporting the earthquake. A report on the radio definitely cannot cause an earthquake. Figure 8.12 shows the result.

Once the edge between E and R has been given a direction the resulting graph is a DAG. This completes the structure learning process. The next step in the learning process is to determine or estimate the parameters of the model in order to obtain a fully specified Bayesian network.

### 8.2.6 PC\* Algorithm

To speed up the structure learning process various heuristic improvements of the straightforward incremental testing scheme have been developed (Spirtes et al. 2000).

One of the main improvements is to identify the conditioning set  $S_{XY}$  using an undirected graph specifying pairs of variables that have been identified as (conditional) independent given previous test results. Thus, an undirected graph describing the current set of neighbors of each variable is maintained.

This neighbor graph may be updated each time an independence statement is identified (or after the completion of the sequence of tests performed for a fixed cardinality of the conditioning set), i.e., each independence test not rejecting the hypothesis. Hence, the conditional independence of  $X$  and  $Y$  is only tested conditional on subsets of the neighbors of  $X$  and  $Y$  in the undirected graph. This can significantly reduce the number of independence tests performed. With the improvement described above the algorithm is referred to as the PC\* algorithm (Spirtes et al. 2000).

Similarly, the order in which we try out the possible conditioning sets of a fixed cardinality may be selected according to how likely they are to cause independence for the edge under consideration. For instance, the heuristic rule that the variables of the conditioning set should be strongly correlated with both endpoints of the edge being tested may be used.

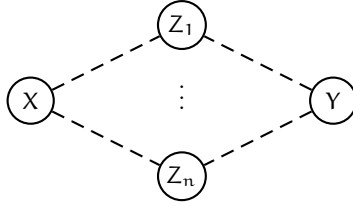
Due to the nature of the testing scheme, the conditioning set  $S_{XY}$  for an identified independence relation  $X \perp\!\!\!\perp Y | S_{XY}$  is minimal in the sense that no proper subset of  $S_{XY}$  makes  $X$  and  $Y$  independent. This is an important property that is exploited by the NPC algorithm.

### 8.2.7 NPC Algorithm

The NPC algorithm (Steck & Tresp 1999) is an extension of the PC algorithm. The additional feature of the NPC algorithm over the PC algorithm is the introduction of the notion of a *necessary path condition* (Steck & Tresp 1999) for the absence of an edge.

#### Necessary Path Condition

Informally, the necessary path condition for the absence of an edge says that in order for two variables  $X$  and  $Y$  to be independent (in a DAG faithful data set) conditional on a minimal set  $S_{XY}$ , there must exist a path between  $X$  and every  $Z \in S_{XY}$  (not crossing  $Y$ ) and between  $Y$  and every  $Z \in S_{XY}$  (not crossing  $X$ ), see Figure 8.13. Otherwise, the inclusion of each  $Z$  in  $S_{XY}$  is unexplained. Thus, in order for an independence relation to be valid, a number of edges (or paths) are required to be present in the graph. This is the *necessary path condition*.



**Fig. 8.13.** The necessary path condition says that in order for  $X \perp\!\!\!\perp Y | \{Z_1, \dots, Z_n\}$  to be valid, there should for each  $Z_i, i = 1, \dots, n$  exist a path between  $X$  and  $Z_i$  not crossing  $Y$  and vice versa.

The necessary path condition introduces the concept of an *ambiguous edge*. An edge  $(X, Y)$  is ambiguous if the absence of  $(X, Y)$  depends on the presence of an edge  $(X', Y')$ , and vice versa. In that case,  $(X, Y)$  and  $(X', Y')$  are said to be interdependent. An ambiguous edge indicates inconsistency in the set of independence relations derived by the statistical tests. A maximal set of interdependent ambiguous edges is denoted an *ambiguous region*. The necessary path condition is probably better explained by the following example.

*Example 8.10.* Assume we are given the set of independence relations  $\mathcal{M}_{\perp\!\!\!\perp}$  over the variables  $\{\text{Tub\_or\_cancer}, \text{Tuberculosis}, \text{Cancer}, \text{X\_ray}\}$  from the Asia example (Example 4.2 on page 68) where

$$\begin{aligned} \mathcal{M}_{\perp\!\!\!\perp} = \bigg\{ & \text{X\_ray} \perp\!\!\!\perp \text{Tub\_or\_cancer} | \{\text{Cancer}, \text{Tuberculosis}\}, \\ & \text{X\_ray} \perp\!\!\!\perp \text{Tuberculosis} | \text{Tub\_or\_cancer}, \\ & \text{X\_ray} \perp\!\!\!\perp \text{Cancer} | \text{Tub\_or\_cancer} \bigg\}. \end{aligned} \quad (8.3)$$

The set  $\mathcal{M}_{\perp\!\!\!\perp}$  specifies the independence relations induced by the quantification of the model (i.e., by the conditional probability distributions on the variables of the model given their parents). The CDIR

$$\text{X\_ray} \perp\!\!\!\perp \text{Tub\_or\_cancer} | \{\text{Cancer}, \text{Tuberculosis}\}$$

follows from the fact that **Tub\_or\_cancer** is a deterministic function of the variables **Tuberculosis** and **Cancer**. That is, whenever the states of **Tuberculosis** and **Cancer** are given, the state of **Tub\_or\_cancer** is known and hence independent of the state of **X\_ray**. Assume further that the collider

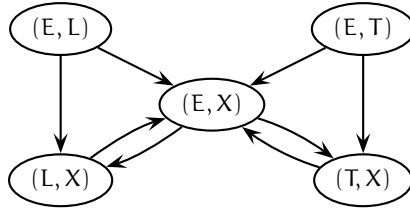
$$\text{Tuberculosis} \rightarrow \text{Tub\_or\_cancer} \leftarrow \text{Cancer}$$

is known to be present, see e.g. Figure 8.16.

The set  $\mathcal{M}_{\perp}$  consists of three independence statements, which are inconsistent (in the rest of this section we use E as short for **Tub\_or\_cancer**, L as short for **Cancer**, and T as short for **Tuberculosis**). The absence of the edge between E and X depends on the presence of the edges (E, L), (E, T), (X, L), and (X, T) according to the necessary path condition. Contrary to this, the absence of the edge between X and T depends on the presence of the edges (E, X) and (E, T). Similarly, the absence of the edge between X and L depends on the presence of the edges (E, X) and (E, L).

The interdependencies between edges induced by the set of conditional independence statements  $\mathcal{M}_{\perp}$  may be displayed as a directed graph  $\mathcal{G}_{\mathcal{M}_{\perp}} = (V, E)$  where each vertex  $v \in V$  corresponds to an edge (X, Y) in  $\mathcal{G}$  and each directed edge  $(u, v) \in E$  specifies that the absence of  $v$  in  $\mathcal{G}$  depends on the presence of  $u$  in  $\mathcal{G}$ . The graph  $\mathcal{G}_{\mathcal{M}_{\perp}}$  is referred to as the *condition graph*.

*Example 8.11.* Figure 8.14 shows the condition graph over  $\mathcal{M}_{\perp}$  in Equation 8.3. Notice that vertices (L, X) and (E, X) as well as (T, X) and (E, X) are connected by two directed edges.



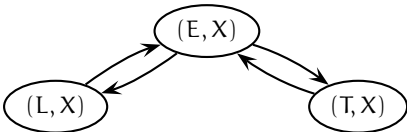
**Fig. 8.14.** The condition graph over  $\mathcal{M}_{\perp}$ .

The condition graph shows how the absence of each edge depends on the presence of other edges.

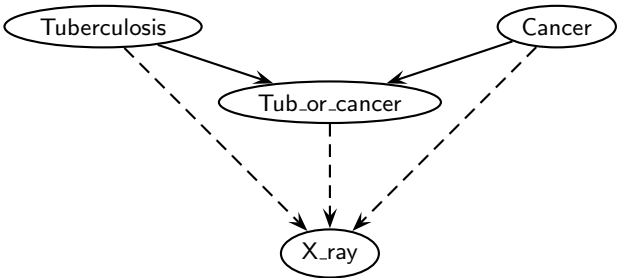
When a vertex  $v$  in  $\mathcal{G}_{\mathcal{M}_{\perp}}$  does not have a parent, it implies that the absence of the edge represented by  $v$  does not depend on the presence of any other edges. Hence, the independence statement related to the absence of the edge represented by  $v$  satisfies the necessary path condition.

The set of ambiguous regions can be identified as the strongly connected components of  $\mathcal{G}_{\mathcal{M}_{\perp}}$  where a *strongly connected component* is a maximal subgraph in which every vertex is connected to every other vertex by a directed path.

*Example 8.12.* Figure 8.15 shows the strongly connected component of the condition graph of Figure 8.14. The strongly connected component consists of vertices (L, X), (E, X), and (T, X). This set of vertices represents an ambiguous region over the corresponding edges.

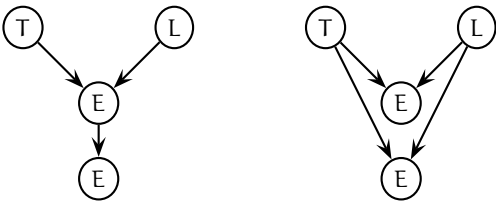


**Fig. 8.15.** The strongly connected component of the condition graph in Figure 8.14.



**Fig. 8.16.** Ambiguous edges in the skeleton due to the deterministic relation between Cancer, Tuberculosis, and Tub\_or\_cancer.

The graph of Figure 8.16 illustrates an alternative graphical representation of the ambiguous region consisting of three edges. The graph does not, however, illustrate how the absence of an edge depends on the presence of another set of edges.



**Fig. 8.17.** The two possible resolutions of the ambiguous region.

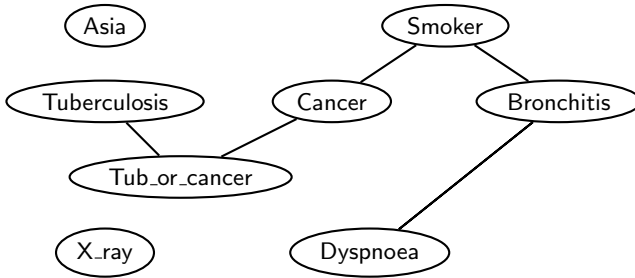
The two possible resolutions of the ambiguous region are shown in Figure 8.17. The ambiguous region may be resolved by including either edge  $(E, X)$  or edges  $(L, X)$  and  $(T, X)$  in the graph. The minimal resolution is  $(E, X)$ .

An ambiguous region is resolved by including a minimal number of ambiguous edges in order to satisfy a maximal number of independence relations. In



a graphical representation ambiguous regions should, for instance, have different color as they consist of independent sets of ambiguous edges. A resolution of an ambiguous region is a minimal set of edges which will remove all ambiguous edges. A resolution is to include some of the ambiguous edges in the graph in order to be able to make as many independence relations as possible fulfill the necessary path condition.

*Example 8.13.* Figure 8.18 shows the skeleton of the graph identified by the PC algorithm based on a (sufficiently large) sample  $\mathcal{D}$  generated from the Asia network (Figure 4.2 on page 69).



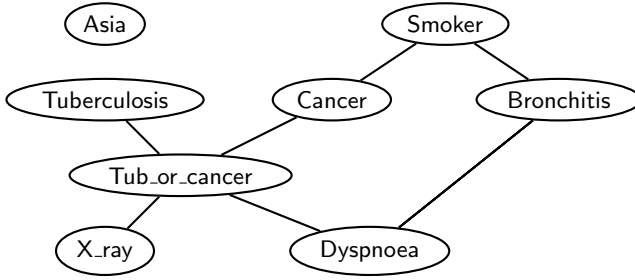
**Fig. 8.18.** Skeleton representing the CDIRs  $\mathcal{M}_{\mathcal{D}}$  generated from  $\mathcal{D}$  by the PC algorithm.

Comparing the skeleton of Figure 8.18 with the skeleton of the acyclic, directed graph of Figure 4.2 we notice that three edges seem to be missing in Figure 8.18. These are the edges (Asia, Tuberculosis), (X\_ray, Tub\_or\_cancer), and (Dyspnoea, Tub\_or\_cancer). The edge (Asia, Tuberculosis) is too weak not to be rejected by the hypothesis test whereas the edges (X\_ray, Tub\_or\_cancer) and (Dyspnoea, Tub\_or\_cancer) are absent due to the (deterministic) relation between Tub\_or\_cancer, Tuberculosis, and Cancer as explained in Example 8.10.

Figure 8.19 shows the skeleton of the graph identified by the NPC algorithm based on the same data set  $\mathcal{D}$ . The edge (Asia, Tuberculosis) is missing for the reasons explained above whereas the (deterministic) relation between Tub\_or\_cancer, Tuberculosis, and Cancer has induced two ambiguous regions.

The ambiguous regions can be resolved by selecting the minimal resolution in each region.

In the above presentation we have assumed that at most a single conditional independence statement is generated for each pair of variables. If multiple conditional independence statements are generated it is necessary to introduce a more complicated graphical notion where it is possible to represent the fact that an edge may depend on different subsets of edges (one subset of edges corresponding to each independence statement).



**Fig. 8.19.** Skeleton representing the CDIRs  $\mathcal{M}_{\mathcal{D}}$  generated from  $\mathcal{D}$  by the NPC algorithm after selecting minimal resolutions.

In order to increase reliability and stability of the NPC algorithm multiple independence statements may be generated for each pair of variables. This can, for instance, be achieved by completing the iteration step for a fixed cardinality of the conditioning set even if an independence statement is found.

If one of the independence relations satisfies the necessary path condition, then the independence hypothesis is not rejected. Otherwise, an ambiguous edge is created.

The PC and NPC structure learning algorithms can be considered as extensions of the WL (Wermuth & Lauritzen 1983) and SGS (Spirtes et al. 2000) algorithms.

### 8.3 Batch Parameter Learning From Data

Parameter estimation in a Bayesian network  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  is the task of estimating the values of parameters  $\Theta$  corresponding to DAG structure  $\mathcal{G}$  and distributions  $\mathcal{P}$  from a database of cases  $\mathcal{D} = \{c^1, \dots, c^N\}$ .

Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  be a Bayesian network with parameters  $\Theta = \{\Theta_i\}$  where  $\Theta_i = \{\Theta_{ij}\}$  and  $\Theta_{ij} = \{\theta_{ijk}\}$  such that  $\theta_{ijk} = P(X_i = k | \text{pa}(X_i) = j)$  for each  $i, j, k$ . Batch parameter learning from data is to estimate the value of  $\theta_{ijk}$  from  $\mathcal{D}$ .

When each case  $c^i \in \mathcal{D}$  is *complete* maximum likelihood parameter estimation is simple (a case  $c^i$  is complete when  $c^i$  assigns a value to each variable  $X_i \in \mathcal{X}$ ). The basic idea of parameter learning is illustrated in the following example.

*Example 8.14.* Table 8.2 on page 234 shows the sufficient statistics for testing marginal independence of  $X$  and  $Y$  in Example 8.4. From this example we may determine a maximum likelihood estimate  $\hat{P}(X = y | Y = y)$  of the conditional probability of  $X = y$  given  $Y = y$  as follows

$$\begin{aligned}
\hat{P}(X = y | Y = y) &= \frac{\hat{P}(X = y, Y = y)}{\hat{P}(Y = y)} \\
&= \frac{\frac{n(X=y, Y=y)}{N}}{\frac{n(Y=y)}{N}} \\
&= \frac{n(X = y, Y = y)}{n(Y = y)}.
\end{aligned}$$

From Table 8.2 we have  $n(X = y) = 87$  and  $n(X = y, Y = y) = 3$ . Estimating the conditional probability parameter  $\hat{\theta}_{Y=y|X=y} = \hat{P}(Y = y | X = y)$  proceeds as

$$\hat{P}(Y = y | X = y) = \frac{n(Y = y, X = y)}{n(X = y)} = \frac{3}{87} = 0.034.$$

The remaining parameters of  $P(Y|X)$  are estimated in a similar way.

### 8.3.1 Expectation-Maximization Algorithm

Parameter estimation in the case of missing values may be performed using the Expectation-Maximization (EM) algorithm (Lauritzen 1995). The EM algorithm is well-suited for calculating maximum likelihood (ML) and maximum a posteriori (MAP) estimates in the case of missing data. The EM algorithm proceeds by iterating two steps: the expectation E-step and the maximization M-step.

Let  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$  be a Bayesian network for which we would like to estimate the parameters  $\Theta$  of  $\mathcal{P}$  from a database of cases  $\mathcal{D}$ . The estimation of the parameters  $\Theta$  from  $\mathcal{D}$  proceeds, as mentioned above, by iterating the E-step and the M-step. Given an initial assignment to the parameters  $\Theta$ , the E-step is to compute the expected sufficient statistics under  $\Theta$ , while the subsequent M-step is to maximize the log-likelihood of the parameters under the expected sufficient statistics. These two steps are alternated iteratively until a stopping criterion is satisfied.

In the case of missing data, the log-likelihood function of the parameters is a linear function in the sufficient marginals (Lauritzen 1995). The log-likelihood function  $l(\Theta)$  of the parameters  $\Theta$  given the data  $\mathcal{D} = \{c^1, \dots, c^N\}$  and DAG  $\mathcal{G}$  is

$$\begin{aligned}
l(\Theta) &= \sum_{l=1}^N \log P(c^l | \Theta) \\
&= \sum_{l=1}^N \sum_{i=1}^{|V|} \log P(X_i = x_i^l | \text{pa}(X_i) = x_{\text{pa}(X_i)}^l, \Theta_i, c^l) \\
&= \sum_{i=1}^{|V|} l(\Theta_i),
\end{aligned}$$

where  $l(\Theta_i) = \sum_{l=1}^N \log P(X_i = x_i^l | \text{pa}(X_i) = x_{\text{pa}(X_i)}^l, \Theta_i, c^l)$  assuming the parameters  $\Theta_i$  to be independent and  $(x_i^l, x_{\text{pa}(X_i)}^l)$  are the values of  $(X_i, \text{pa}(X_i))$  in the  $l$ th (possibly incomplete) case of  $\mathcal{D}$ .

For Bayesian networks, the E-step of the EM algorithm is to compute expected counts (expected sufficient statistics for a complete database), where expectation is taken with respect to the joint distribution over  $V$  under the current parameter values  $\Theta$  and observed data  $\mathcal{D}$

$$\mathbb{E}_{\Theta}(N_{ijk}) = \sum_{l=1}^N P(X_i = k, \text{pa}(X_i) = j | c^l, \Theta_i, G),$$

where  $N_{ijk}$  is the count for  $(X_i, \text{pa}(X_i)) = (k, j)$  and  $c^l$  is the  $l$ th case of  $\mathcal{D}$ . Next, the M-step computes new estimates  $\theta_{ijk}^*$  of  $\theta_{ijk}$  interpreting the expected sufficient statistics as actual sufficient statistics from a complete database of cases

$$\theta_{ijk}^* = \frac{\mathbb{E}_{\Theta}(N_{ijk})}{\sum_{k=1}^{|X_i|} \mathbb{E}_{\Theta}(N_{ijk})}.$$

The E-step and M-step are iterated until convergence of  $l(\Theta)$  (or until a limit on the number of iterations is reached).

We say convergence is achieved when the difference between the log-likelihoods of two consecutive iterations is less than or equal to the numerical value of a log-likelihood threshold  $\delta$  times the log-likelihood, i.e.,

$$l_i(\Theta) - l_{i+1}(\Theta) \leq \delta |l_{i+1}(\Theta)|$$

where  $l_i(\Theta)$  is the log-likelihood of  $\Theta$  after the  $i$ th iteration and  $l_{i+1}(\Theta)$  is the log-likelihood of  $\Theta$  after the  $(i+1)$ st iteration.

Alternatively, an upper limit on the number of iterations can be specified in order to ensure that the procedure terminates.

*Example 8.15 (Toss of a Coin).* Consider the task of predicting the toss of a coin. Having no additional knowledge of the coin we would assume it to be fair. Hence, we assume heads and tails to be equally likely as the result of tossing the coin. Let  $X$  be a discrete random variable with two states **heads** and **tails** representing the outcome of a toss of the coin.

If we have observed the result of ten tosses of the coin we can use this data to predict the result of a subsequent toss of the coin. Assume we make the following sequence of observations on previous tosses of the coin

tails, tails, heads, tails, heads, tails, N/A, tails, tails, heads,

where N/A indicates a missing observation in the seventh throw, i.e., we know the coin was tossed, but for some (random) reason we do not have access to the result. From this sequence of observations we want to estimate the distribution of  $X$ .

Since we have no extra knowledge about the coin we assume a uniform prior distribution on  $X$ . Hence, the initial parameter assignment is set to  $P(X) = (0.5, 0.5)$ , i.e.,  $\Theta = \{\theta_{\text{tails}} = 0.5, \theta_{\text{heads}} = 0.5\}$ .

The estimated distribution after running the EM algorithm with the data and parameter setting described above is  $P(X) = (0.74992, 0.25008)$  with an experience count  $\alpha = 10$ . This distribution is the result of five iterations of the EM algorithm with  $\delta = 0.0001$  and

$$\begin{aligned} l_1(\Theta) &= -5.54518 \\ l_2(\Theta) &= -4.548 \\ l_3(\Theta) &= -4.50078 \\ l_4(\Theta) &= -4.49877 \\ l_5(\Theta) &= -4.49868. \end{aligned}$$

The parameter estimation is completed after five iterations of the EM algorithm as described above.

Taking the observations on the coin into account, we predict tails to be approximately three times as likely as heads.

In the EM algorithm the log-likelihood function  $l(\Theta)$  of the model given data is used as a quality measure to compare different parameterizations of the same network structure. When the increase in quality of the parameterization between subsequent iteration steps is below a threshold, the EM algorithm terminates. The log-likelihood function is well suited for this purpose. However, the log-likelihood quality measure does not take network complexity into account. Thus, the log-likelihood measure is not well suited for model selection due to overfitting from using a too-complex network structure. The log-likelihood measure will take its maximum value for a complete graph.

Instead of using log-likelihood for model selection, Akaike's Information Criterion (AIC) or the Jeffreys–Schwarz criterion, also called the Bayesian Information Criterion (BIC), may be used. The AIC score is computed as  $l(\Theta) - \kappa$  and the BIC score is computed as  $l(\Theta) - \frac{1}{2}\kappa \log N$  where  $\kappa$  is the number of free parameters in the network and  $N$  is the number of cases in the database. The number of free parameters  $\kappa$  is defined as

$$\kappa = \sum_{X \in V} (||X|| - 1) \prod_{Y \in \text{pa}(X)} ||Y||.$$

### 8.3.2 Penalized EM Algorithm

When both data and domain expert knowledge are available, both of these two sources of knowledge should be taken into consideration by the parameter estimation algorithm. This can be achieved using the *penalized* EM algorithm.

Domain expert knowledge on the parameters of a conditional probability distribution is specified in the form of a Dirichlet probability distribution and

an *experience table*. For each variable  $X_i$ , the distribution  $P(X_i | \text{pa}(X_i)) = \{P(X_i = k | \text{pa}(X_i) = j)\}$  and the *experience counts*  $\alpha_{i1}, \dots, \alpha_{im}$  where  $m = \|\text{pa}(X_i)\|$  associated with  $X_i$  are used to specify the prior expert knowledge. The size of the experience count  $\alpha_i$  indicates the weight of the domain expert knowledge. The experience table over a variable  $X_i$  and its parent variables  $\text{pa}(X_i)$  indicates the experience related to the child distribution for each possible configuration of  $\text{pa}(X_i)$ .

In the case of expert knowledge, the E-step does not change whereas the M-step becomes

$$\theta_{ijk}^* = \frac{\alpha_{ijk} + \mathbb{E}_{\Theta}(N_{ijk})}{\sum_{k=1}^{\|X_i\|} (\alpha_{ijk} + \mathbb{E}_{\Theta}(N_{ijk}))},$$

where  $\alpha_{ijk} = P(X_i = k | \text{pa}(X_i) = j) \alpha_{ij}$  is the initial count for  $(X_i, \text{pa}(X_i)) = (k, j)$ . Thus, the M-step is changed to take the expert knowledge into account.

*Example 8.16.* Consider again the problem of predicting the result of a coin toss. Assume we have reason to believe that the coin is not fair. Instead of assuming a uniform prior distribution on the parameters, we will assume a non-uniform prior on  $X$ , e.g. we assume the parameter assignment is  $P(X) = (0.75, 0.25)$  with an experience count of  $\alpha = 5$ . This will serve as the initial parameter assignment.

The estimated distribution is  $P(X) = (0.75, 0.25)$  with an experience count  $\alpha = 15$ . This distribution is the result of only two iterations of the EM algorithm with  $\delta = 0.0001$  and

$$\begin{aligned} l_1(\Theta) &= -4.49868 \\ l_2(\Theta) &= -4.49868. \end{aligned}$$

The parameter estimation is completed after only two iterations of the EM algorithm as described above.

Taking the observations on the coin and the additional knowledge of the coin into account, we predict *tails* to be three times as likely as *heads*.

The penalized EM algorithm is useful for combining expert domain knowledge and data in parameter estimation. It is, however, important to be careful when using the penalized EM algorithm as illustrated by the following example.

*Example 8.17.* Assume we need to estimate the conditional probability distributions of a network with two dependent variables  $X$  and  $Y$ . To model the dependency between variables  $X$  and  $Y$  we have either the network in Figure 8.20(a) or the network in Figure 8.20(b).

From the point of view of modeling the joint probability distribution over variables  $X$  and  $Y$ , the choice of network does not matter as the two models are equivalent. Assume the complete database of cases to be used in the parameter estimation has sufficient statistics as shown in Table 8.3. The database



**Fig. 8.20.** Two equivalent DAGs over  $X$  and  $Y$ .

Y	X		
	$x_0$	$x_1$	
$y_0$	0	2	2
$y_1$	4	2	6
$y_2$	6	3	9
	10	7	17

**Table 8.3.** Sufficient statistics for estimating the distributions of  $X$  and  $Y$ .

consists of 17 complete cases, i.e., no missing values. Notice that the configuration  $(x_0, y_0)$  does not appear in the database.

The probability of the configuration  $(x_0, y_0)$  will be zero in both networks if the EM algorithm is used for the estimation. The penalized EM algorithm may be used to avoid zero probabilities in the joint probability distribution. The trick is to assign a positive probability distribution to the initial parameter values and a non-zero value to the experience counts. The values of the experience counts should be chosen with care though.

Assume we decide to assign a uniform probability distribution to the parameters, e.g.,  $P(X) = (1/2, 1/2)$ ,  $P(Y|X = x_0) = (1/3, 1/3, 1/3)$ , and  $P(Y|X = x_1) = (1/3, 1/3, 1/3)$  for the network in Figure 8.20(a). To avoid a zero probability for the configuration  $(x_0, y_0)$  we assign experience counts as  $\alpha_X = 1$ ,  $\alpha_{Y0} = 1$  and  $\alpha_{Y1} = 1$ . The resulting joint probability distribution over  $X$  and  $Y$  is shown in the second column of Table 8.4.

X	Y			
$x_0$	$y_0$	0.0177	0.0216	0.0093
$x_0$	$y_1$	0.2298	0.2262	0.2315
$x_0$	$y_2$	0.3359	0.3370	0.3426
$x_1$	$y_0$	0.1215	0.1080	0.1204
$x_1$	$y_1$	0.1215	0.1257	0.1204
$x_1$	$y_2$	0.1736	0.1815	0.1759

**Table 8.4.** Joint probability distributions over  $X$  and  $Y$ .

If we use the same approach on the network in Figure 8.20(b), then the resulting joint probability distribution over  $X$  and  $Y$  is shown in the third column of Table 8.4.

It is clear from Table 8.4 that the approach taken does not produce the same results for two equivalent models given complete data and a uniform prior. The problem is the value assigned to the experience counts.

Instead of assigning the value 1 to all experience counts, we assign the value  $1/||\text{pa}(X)||$  to each parent configuration of  $X$  and value  $1/||\text{pa}(Y)||$  to each parent configuration of  $Y$ . This approach will ensure that the two equivalent networks in Figure 8.20 represent the same joint probability distribution over  $X$  and  $Y$  after EM learning. With this approach, the result is the same for both models and it is shown in the last column of Table 8.4.

## 8.4 Sequential Parameter Learning

Sequential parameter learning or parameter adaptation is the task of sequentially updating the parameters of the conditional probability distributions of a Bayesian network when the structure and an initial specification of the conditional probability distributions are given in advance. We consider a Bayesian approach to sequential parameter (Spiegelhalter & Lauritzen 1990, Cowell et al. 1999).

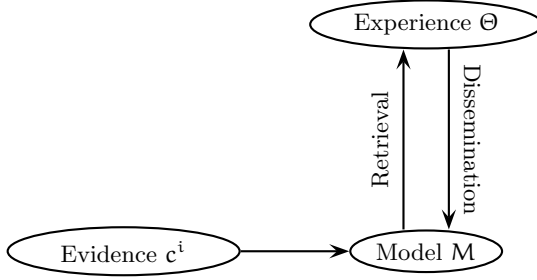
In sequential learning, experience is extended to include both quantitative expert knowledge and past cases (e.g. from EM learning). Thus, the result of EM learning may be considered as input for sequential learning.

Let  $X_i$  be a variable with  $n$  states, then the prior belief in the parameter vector  $\Theta_{ij} = (\theta_{ij1}, \dots, \theta_{ijn})$ , i.e., the conditional probability distribution of a variable  $X_i$  given its parents  $\text{pa}(X_i) = j$ , is specified as an  $n$ -dimensional Dirichlet distribution  $\mathcal{D}(\alpha_{ij1}, \dots, \alpha_{ijn})$ . This distribution is represented using a single experience count  $\alpha_{ij} = 1/||\text{pa}(X_i)||$  (*equivalent sample size*) and the initial distribution  $P(X_i | \text{pa}(X_i) = j)$ . The experience count  $\alpha_{ijk}$  for a particular state  $k$  of  $X_i$  given  $\text{pa}(X_i) = j$  is  $\alpha_{ijk} = \alpha_{ij} P(X_i = k | \text{pa}(X_i) = j)$ . This setting is similar to the setting of the EM algorithm.

Parameter adaptation proceeds by updating the experience associated with the parameters and subsequently updating the parameters to reflect the new experience. The process of updating the experience associated with a distribution is referred to as *retrieval of experience*. *Dissemination of experience* is the process of calculating prior conditional probability distributions for the variables in the Bayesian network given the experience, and it proceeds by setting each parameter equal to the mean of the corresponding updated Dirichlet distribution, i.e.,  $\theta_{ijk}^*$ , as shown below. See Figure 8.21 for a graphical representation of dissemination and retrieval of experience.

After a complete observation  $(X_i, \text{pa}(X_i)) = (k, j)$ , the posterior belief in the distribution is updated as  $\alpha_{ijk}^* = \alpha_{ijk} + 1$  and  $\alpha_{ijl}^* = \alpha_{ijl}$  for  $l \neq k$ . After





**Fig. 8.21.** Retrieval and dissemination of experience.

an incomplete observation, the resulting weighted sum of Dirichlet distributions over the parameters is approximated with a single Dirichlet distribution with the same means and sum of variances as the mixture. The approximation is used in order to avoid the combinatorial explosion, which would otherwise occur when subsequent incomplete observations are made. For each  $i, j, k$ , the updated value  $\theta_{ijk}^*$  of each parameter  $\theta_{ijk}$  is

$$\theta_{ijk}^* = \frac{\alpha_{ijk} + P(X_i = k, \text{pa}(X_i) = j \mid \varepsilon) + \theta_{ijk}(1 - P(\text{pa}(X_i) = j \mid \varepsilon))}{\alpha_{ij} + 1}.$$

The updated equivalent sample size  $\alpha_{ij}^*$  is a function of the means and the sum of variances, see e.g. Cowell et al. (1999) for details on computing the updated  $\alpha_{ij}^*$ . Notice that  $P(X_i = k, \text{pa}(X_i) = j \mid \varepsilon)$  and  $P(\text{pa}(X_i) = j \mid \varepsilon)$  are readily available after a propagation of evidence.

In order to reduce the influence of past and possibly outdated information, an optional feature of fading is provided. Fading proceeds by reducing the experience count before the retrieval of experience takes place. The experience count  $\alpha_{ij}$  is faded by a factor of  $0 < \lambda_{ij} \leq 1$  typically close to one according to  $p_{ij} = P(\text{pa}(X_i) = j)$  such that  $\alpha_{ij}^* = \alpha_{ij}((1 - p_{ij}) + \lambda_{ij}p_{ij})$ . Notice that experience counts corresponding to parent configurations, which are inconsistent with the evidence, are unchanged. The fading factors of a variable  $X_i$  are specified in a separate table including one fading factor for each configuration of  $\text{pa}(X_i)$ .

*Example 8.18.* Consider again the Asia example (Example 4.2 on page 68). Assume we have evidence  $\varepsilon = \{S = \text{no}, A = \text{yes}, D = \text{yes}\}$  on a patient, i.e., a non-smoking patient with dyspnoea who has recently been to Asia. The evidence is entered and propagated followed by an adaptation of parameters. Table 8.5 shows the experience counts for L, B, and S before (i.e., after EM learning using 10,000 randomly generated cases) and after the adaptation with fading factor of  $\lambda = 0.999$  for each distribution.

Note that since  $S$  is an observed variable without parents, the experience count  $\alpha_S$  for  $P(S)$  will converge to  $\frac{1}{\lambda} = 1001$  if  $S = \text{no}$  is observed multiple times.

	$\alpha_S$	$\alpha_L   S=no$	$\alpha_L   S=yes$	$\alpha_B   S=no$	$\alpha_B   S=yes$
Before	10,000	4970.88	5029.12	4970.88	5029.12
After	9,001	4472.71	5029.12	4473.73	5029.12

**Table 8.5.** Experience counts for B, L, and S before and after adaptation.

Sequential updating may be applied to the parameters of conditional probability distributions in mixed Bayesian networks and in influence diagrams when all decisions have been instantiated.

## 8.5 Summary

In this chapter we have considered data-driven modeling as the process of inducing a Bayesian network from data and domain expert knowledge. We have considered this as a two-step learning process where the first step is to induce the structure of the graph of the Bayesian network whereas the second step is to estimate the parameters of the conditional probability distributions induced by the graphical structure of the Bayesian network.

We have considered the constraint-based approach to learning the structure of a Bayesian network from data. In particular we have described in some detail the steps of the PC algorithm. The PC algorithm is based on performing a sequence of statistical hypothesis tests for (conditional) independence. Based on the set of CDIRs derived by the test, the skeleton, the colliders, and derived directions of the graph are identified.

Since the result of the PC algorithm (i.e., the PDAG) is rather sensitive to errors in the CDIRs the notion of a necessary path condition for the absence of an edge in the skeleton of the induced graph is introduced. The necessary path condition produces the NPC algorithm, which has also been described in some detail.

The graph resulting from structure learning defines the set of conditional probability distributions of the Bayesian network. The parameters of this set of distributions may be set manually, but more often the parameters of the distributions will be estimated from the same database of cases as used by the structure learning algorithm. We have described the EM algorithm and the penalized EM algorithm for estimating the parameters of a conditional probability distribution from data.

Finally, we have described a Bayesian approach for adaptation of parameters as the model is used.

In the next part of the book we consider different methods for analyzing probabilistic networks. This includes methods for conflict analysis, sensitivity analysis, and value of information analysis.

## Exercises

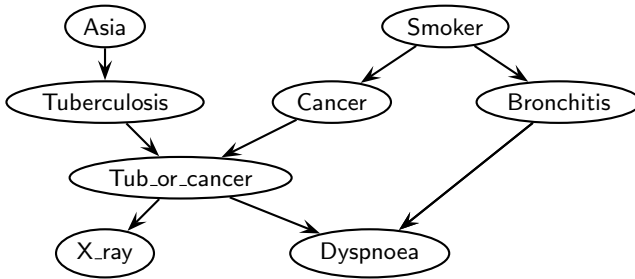
**Exercise 8.1.** Let the following set of conditional pairwise independence statements be the result of performing statistical independence tests  $\mathcal{M}_{\perp}$  on a set of variables:

$$\mathcal{M}_{\perp} = \left\{ A \perp\!\!\!\perp C \mid \{\}, C \perp\!\!\!\perp S \mid \{\}, F \perp\!\!\!\perp S \mid \{A\}, T \perp\!\!\!\perp S \mid \{A\}, T \perp\!\!\!\perp F \mid \{C\} \right\}.$$

For each independence statement  $X \perp\!\!\!\perp Y \mid S_{XY}$ , the conditioning set  $S_{XY}$  is minimal.

- Identify the skeleton of the graph of the network.
- Identify colliders.
- Identify derived directions.
- Identify remaining undirected edges according to your interpretation of the problem domain.

**Exercise 8.2.** Generate 10,000 sample cases from the Asia network shown in Figure 8.22 (see Example 4.2 on page 68 for more details).



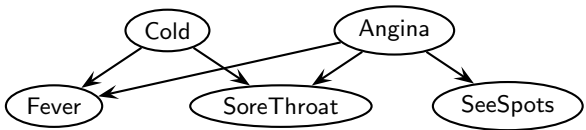
**Fig. 8.22.** A graph specifying the independence and dependence relations of the Asia example.

The Asia network consists of the three hypothesis variables **Bronchitis**, **Cancer**, and **Tuberculosis**. The risk factors are **Smoking** and a recent visit to **Asia** while the symptoms of the network are **X-ray** and **Dyspnoea**. The risk factors and symptoms are the possible observations a physician can make on a patient.

- Use a software package for learning the equivalence class of DAGs representing the data generated. Specify expert knowledge on the structure of the DAG as constraints.
- Resolve ambiguous regions.
- Complete orientation of the DAG.

(d) Specify expert knowledge on the distributions of the model and estimate the parameters from the data generated.

**Exercise 8.3.** Consider the network in Figure 8.23. Assume the network is the result of learning from a complete database with 1000 cases and let  $l(\Theta) = -964$ .



**Fig. 8.23.** The Angina network.

- (a) Compute the AIC score.
- (b) Compute the BIC score.
- (c) Compare the AIC and BIC scores. Explain the difference.

**Exercise 8.4.** Assume we plan to pick up mushrooms to prepare for a nice dinner. In the process we want to classify each mushroom as either edible or poisonous. We want to construct a network for classifying each mushroom based on a database of mushrooms. Assume Table 8.6 to Table 8.9 specify the sufficient statistics of a database we found on the Internet.

Class	n
edible	5333
poisonous	4667

**Table 8.6.** Sufficient statistics for the class variable.

- (a) Construct a model for classifying mushrooms based on the data in Table 8.6 to Table 8.9.
- (b) What is the probability of a mushroom with no odor being edible?

Population	Class	
	edible	poisonous
abundant	587	0
clustered	389	75
numerous	480	0
scattered	1173	420
several	1440	3384
solitary	1264	788

**Table 8.7.** Sufficient statistics for the class variable and Population.

Cap_Shape	Class	
	edible	poisonous
bell	478	56
conical	0	5
convex	2453	2034
flat	2098	1853
knobbed	267	719
sunken	37	0

**Table 8.8.** Sufficient statistics for the class variable and Cap\_Shape.

Odor	Class	
	edible	poisonous
almond	475	0
anise	475	0
creosote	0	229
fishy	0	685
foul	0	2567
musty	0	57
none	4383	141
pungent	0	303
spicy	0	685

**Table 8.9.** Sufficient statistics for the class variable and Odor.

## Part III

---

### Model Analysis

## Conflict Analysis

---

It is difficult or even impossible to construct models covering all aspects of (complex) problem domains of interest. A model is therefore most often an approximation of a problem domain that is designed to be applied according to the assumptions as determined by the background condition or context of the model. If a model is used under circumstances not consistent with the background condition, the results will in general be unreliable. The evidence need not be inconsistent with the model in order for the results to be unreliable. It may be that evidence is simply in conflict with the model. This implies that the model in relation to the evidence may be weak and therefore the results may be unreliable.

Evidence driven conflict analysis is used to detect possible conflicts in the evidence or between the evidence and the model. If a possible conflict is detected we should alert the user that the model given the evidence may be weak or even misleading. In this way conflict analysis can also be used for model revision.

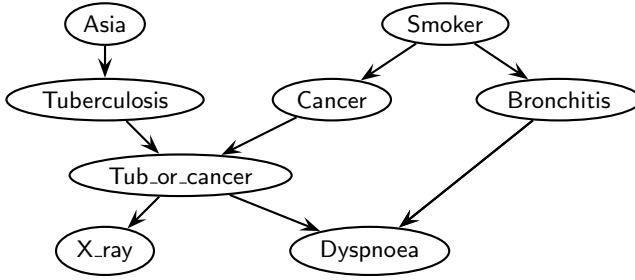
Hypothesis driven conflict analysis is used to identify findings acting in favor of or against a hypothesis. If the evidence set consists of a large number of findings, it may be crucial to identify which individual findings act in favor of or against a hypothesis.

In this chapter we use the Asia example to illustrate the concepts of evidence and hypothesis driven conflict analysis in Bayesian networks.

*Example 9.1 (Asia).* As an example we apply conflict analysis to the Asia example shown in Figure 9.1 (see Example 4.2 on page 68 for more details).

Assume we see a smoking patient with no shortness of breath and a negative X-ray result, i.e., the initial set of evidence is  $\varepsilon = \{\text{Dyspnoea} = \text{no}, \text{Smoker} = \text{yes}, \text{X\_ray} = \text{no}\}$ . In the remainder of this section we write  $\varepsilon = \{\varepsilon_D, \varepsilon_S, \varepsilon_X\}$  for short.

From our knowledge about the problem domain and the assumptions of the model, we would say that the findings are in conflict. The patient visited the chest clinic, but she does not have any of the symptoms even though



**Fig. 9.1.** A graph specifying the independence and dependence relations of the Asia example.

she is a smoker. A propagation of the evidence produces posterior probability distributions over the diseases  $P(B = \text{yes}|\epsilon) = 0.25$ ,  $P(L = \text{yes}|\epsilon) = 0.089$ , and  $P(T = \text{yes}|\epsilon) = 0.009$ . This does not disclose a possible conflict, but only indicates that the most likely disease the patient is suffering from is bronchitis. Using the model only, we cannot distinguish between flawed evidence, a case not covered by the model, or a rare case.

In Section 9.1 we describe evidence driven conflict analysis. A *conflict measure* designed to be efficient to compute and to give indications of possible conflicts in evidence is introduced. Possible conflicts should be detected and traced or explained as rare cases that the model may not cover well. In Section 9.2 we describe hypothesis driven conflict analysis. A *cost-of-omission measure* is introduced. This measure is useful for relating the impact of findings on a hypothesis variable. In addition, we describe how to investigate the impact of a finding on the probability of a hypothesis.

## 9.1 Evidence Driven Conflict Analysis

The objective in evidence driven conflict analysis is to detect possible conflicts in a set of evidence. As a tool for detecting possible conflicts, we want a conflict measure which is easy to calculate and which gives a reliable indication of a possible conflict.

### 9.1.1 Conflict Measure

In order to detect a possible conflict we need to compare the results obtained from our best model with the results obtained from an alternative model. This model is referred to as a *straw model*. A straw model is a simple and computationally efficient model used as an alternative model in the detection of possible conflicts.



In the design of the conflict measure we make the assumption that for the *normally* (according to the model) behaving evidence it is the case that  $P(\varepsilon_i|\varepsilon_j) > P(\varepsilon_i)$  where  $\varepsilon_i$  and  $\varepsilon_j$ . Based on this assumption and since  $P(\varepsilon_i, \varepsilon_j) = P(\varepsilon_i|\varepsilon_j)P(\varepsilon_j)$ , the conflict measure is designed to indicate a possible conflict when the joint probability of the evidence is less than the product of the probabilities of the individual pieces of evidence given the model. We thus assume that there is a possible conflict between two pieces of evidence  $\varepsilon_i$  and  $\varepsilon_j$ , if

$$\frac{P(\varepsilon_i)P(\varepsilon_j)}{P(\varepsilon_i, \varepsilon_j)} > 1 \Leftrightarrow \log \frac{P(\varepsilon_i)P(\varepsilon_j)}{P(\varepsilon_i, \varepsilon_j)} > 0,$$

i.e.,  $\varepsilon_i$  and  $\varepsilon_j$  are negatively correlated. Thus, we define the conflict measure as

$$\text{conf}(\varepsilon) = \log \frac{P(\varepsilon_i)P(\varepsilon_j)}{p(\varepsilon)},$$

where  $\varepsilon = \{\varepsilon_i, \varepsilon_j\}$ . Notice that we are comparing the joint probability of the evidence with a model where the observed variables are independent (the straw model).

The main assumption is that pieces of evidence are positively correlated such that  $P(\varepsilon) > \prod_{i=1}^n P(\varepsilon_i)$ . With this assumption the general conflict measure is defined as

$$\text{conf}(\varepsilon) = \text{conf}(\{\varepsilon_1, \dots, \varepsilon_n\}) = \log \frac{\prod_{i=1}^n P(\varepsilon_i)}{p(\varepsilon)}.$$

This implies that a positive value of the conflict measure  $\text{conf}(\varepsilon)$  indicates a possible conflict. Notice that the conflict measure is easy to calculate once the evidence  $\varepsilon$  has been propagated in a junction tree representation of the model. The marginal probabilities  $P(\varepsilon_i)$  are available once the junction tree has been initialized and the probability of the evidence  $P(\varepsilon)$  is available as a by-product of message passing, see Section 5.1 for details on propagation of evidence.

Another way to look at the definition of the conflict measure is the following. In the general case, two pieces of evidence  $\varepsilon_i$  and  $\varepsilon_j$  are either

- positively correlated, i.e.,  $P(\varepsilon_i|\varepsilon_j) > P(\varepsilon_i)$ ,
- negatively correlated, i.e.,  $P(\varepsilon_i|\varepsilon_j) < P(\varepsilon_i)$ , or
- independent, i.e.,  $P(\varepsilon_i|\varepsilon_j) = P(\varepsilon_i)$ .

Given these three options, we choose to assume that two pieces of evidence  $\varepsilon_i$  and  $\varepsilon_j$  are positively correlated.

*Example 9.2.* Returning to Example 9.1, the evidence is  $\varepsilon = \{\varepsilon_D, \varepsilon_S, \varepsilon_X\}$ . We compute the conflict measure to be

$$\begin{aligned}
\text{conf}(\varepsilon) &= \text{conf}(\{D = \text{no}, S = \text{yes}, X = \text{no}\}) \\
&= \log \frac{P(D = \text{no})P(S = \text{yes})P(X = \text{no})}{P(\varepsilon)} \\
&= \log \frac{0.56 * 0.5 * 0.89}{0.2} = 0.22 \\
&> 0.
\end{aligned}$$

Thus,  $\text{conf}(\varepsilon)$  indicates a possible conflict in  $\varepsilon$ .

### 9.1.2 Tracing Conflicts

Once a possible conflict has been detected, the origin of the conflict should be determined such that it can be presented to the analyst or user. Tracing the source of a conflict amounts to computing the conflict measure  $\text{conf}(\varepsilon')$  for (all) subsets  $\varepsilon' \subseteq \varepsilon$ .

Tracing the conflict to all subsets of the evidence is a computationally complex problem as the number of subsets increases exponentially with the size of the evidence set. It is not always possible or meaningful to assume monotonicity with respect to conflict in subsets, i.e., no subset  $\varepsilon'' \subseteq \varepsilon'$  with  $\text{conf}(\varepsilon'') > 0$  exists for  $\varepsilon'$  with  $\text{conf}(\varepsilon') \leq 0$ . That is, the monotonicity assumption states that if  $\varepsilon'$  is not in conflict, then no subset of  $\varepsilon'$  is in conflict.

*Example 9.3.* In Example 9.2 a possible conflict was identified, but not traced, i.e., located. That is, after the conflict measure has been found to indicate a possible conflict, the source of the conflict should be traced. This is achieved by computing the conflict measure for different subsets  $\varepsilon'$  of  $\varepsilon$ .

With three pieces of evidence there are three pairs of evidence to consider. The pair  $\varepsilon_{DS} = \{\varepsilon_D, \varepsilon_S\}$  has conflict measure

$$\begin{aligned}
\text{conf}(\varepsilon_D, \varepsilon_S) &= \log \frac{P(D = \text{no})P(S = \text{yes})}{P(D = \text{no}, S = \text{yes})} \\
&= \log \frac{0.56 * 0.5}{0.22} = 0.24,
\end{aligned}$$

the pair  $\varepsilon_{DX} = \{\varepsilon_D, \varepsilon_X\}$  has conflict measure

$$\begin{aligned}
\text{conf}(\varepsilon_D, \varepsilon_X) &= \log \frac{P(D = \text{no})P(X = \text{no})}{P(D = \text{no}, X = \text{no})} \\
&= \log \frac{0.56 * 0.89}{0.52} = -0.04,
\end{aligned}$$

and the pair  $\varepsilon_{DS} = \{\varepsilon_S, \varepsilon_X\}$  has conflict measure

$$\begin{aligned}
\text{conf}(\varepsilon_S, \varepsilon_X) &= \log \frac{P(S = \text{yes})P(X = \text{no})}{P(S = \text{yes}, X = \text{no})} \\
&= \log \frac{0.5 * 0.89}{0.47} = -0.06.
\end{aligned}$$

The (partial) conflicts show that there is a conflict in the pair  $\varepsilon_{DS} = \{\varepsilon_D, \varepsilon_S\}$  while there are no conflicts in the pairs  $\varepsilon_{DX} = \{\varepsilon_D, \varepsilon_X\}$  and  $\varepsilon_{SX} = \{\varepsilon_S, \varepsilon_X\}$ . Hence, the source of the global conflict in  $\text{conf}(\varepsilon)$  can be traced to the partial conflict between  $\varepsilon_D$  and  $\varepsilon_S$ . The finding that the patient is a smoker is in conflict with the finding that the patient is not suffering from dyspnoea (under the assumptions of the model).

Let  $\varepsilon_i$  and  $\varepsilon_j$  be a partitioning of the evidence  $\varepsilon$  into two disjoint subsets such that  $\varepsilon = \varepsilon_i \cup \varepsilon_j$  is the evidence under consideration. The *global conflict*  $\text{conf}(\varepsilon)$  can be computed from *local*  $\text{conf}(\{\varepsilon_i, \varepsilon_j\})$  and *partial conflicts*  $\text{conf}(\varepsilon_i)$  and  $\text{conf}(\varepsilon_j)$

$$\text{conf}(\varepsilon) = \text{conf}(\{\varepsilon_i, \varepsilon_j\}) + \text{conf}(\varepsilon_i) + \text{conf}(\varepsilon_j).$$

This property holds in general and it may be used as a tool for tracing conflicts.

*Example 9.4.* In the example, we have three subsets with partial conflicts computed in Example 9.3  $\text{conf}(\varepsilon_D, \varepsilon_S) = 0.24$ ,  $\varepsilon_{DX} = \{\varepsilon_D, \varepsilon_X\} = -0.04$ , and  $\varepsilon_{DS} = \{\varepsilon_S, \varepsilon_X\} = -0.06$ . The local conflict between  $\{\varepsilon_D, \varepsilon_S\}$  and  $\varepsilon_X$  is

$$\begin{aligned} \text{conf}(\{\varepsilon_D, \varepsilon_S\}, \varepsilon_X) &= \log \frac{P(D = \text{no}, S = \text{yes})P(X = \text{no})}{P(\varepsilon)} \\ &= \log \frac{0.22 * 0.89}{0.2} = -0.02. \end{aligned}$$

The global conflict can be computed from local and partial conflicts as

$$\begin{aligned} \text{conf}(\{\varepsilon_D, \varepsilon_S, \varepsilon_X\}) &= \text{conf}(\{\varepsilon_D, \varepsilon_S\}) + \text{conf}(\{\{\varepsilon_D, \varepsilon_S\}, \varepsilon_X\}) \\ &= 0.24 + (-0.02) = 0.22 \end{aligned}$$

We notice that the finding  $\varepsilon_X$  reduces the global conflict slightly.

### 9.1.3 Conflict Resolution

Typical evidence from a *rare case* may indicate a possible conflict (a rare case is identified as a finding or set of evidence with low (prior) probability). Let  $\varepsilon = \{\varepsilon_1, \dots, \varepsilon_n\}$  be findings for which the conflict measure indicates a possible conflict, i.e.,  $\text{conf}(\varepsilon) > 0$ . Also, let  $h$  be a hypothesis which could explain the findings (i.e.,  $\text{conf}(\varepsilon \cup \{h\}) \leq 0$ ). That is, if we also know the hypothesis  $h$  to be true, then we will not expect a conflict. We compute

$$\text{conf}(\varepsilon \cup \{h\}) = \text{conf}(\varepsilon) + \log \frac{P(h)}{P(h|\varepsilon)}.$$

If  $\text{conf}(\varepsilon) \leq \log \frac{P(h|\varepsilon)}{P(h)}$ , then  $h$  can explain away the conflict where  $\frac{P(h|\varepsilon)}{P(h)}$  is the *normalized likelihood*.

Hypothesis	$P(h)$	$P(h \varepsilon)$	$\log \frac{P(h \varepsilon)}{P(h)}$
Asia = no	0.99	0.99	0
Asia = yes	0.01	0.01	0
Bronchitis = no	0.55	0.75	0.31
Bronchitis = yes	0.45	0.25	-0.59
Cancer = no	0.545	0.1	1.7
Cancer = yes	0.455	0.9	0.68
Tuberculosis = no	0.99	0.999	0.01
Tuberculosis = yes	0.01	0.001	-2.3
Tub_or_cancer = no	0.995	0.9999	0.005
Tub_or_cancer = yes	0.005	0.0001	-3.9

**Table 9.1.** The log-normalized likelihood of each possible instantiation of each variable in Example 9.1.

*Example 9.5.* Table 9.1 shows the log-normalized likelihood of each possible instantiation of each variable in Example 9.1. From this table it is clear that there are five possible explanations of the conflict (some of which have a low log-normalized likelihood).

For instance, the posterior probability of the patient not having bronchitis is  $P(B = \text{no}|\varepsilon) = 0.75$  while the prior probability is  $P(B = \text{no}) = 0.55$ . We compute the logarithm of the normalized likelihood

$$\log \frac{P(h|\varepsilon)}{P(h)} = \log \frac{0.75}{0.55} = 0.31.$$

From this we compute the conflict measure under the hypothesis of the patient not having bronchitis

$$\begin{aligned} \text{conf}(\varepsilon \cup \{h\}) &= \text{conf}(\varepsilon) + \log \frac{P(h)}{P(h|\varepsilon)} \\ &= 0.22 - 0.31 < 0. \end{aligned}$$

Thus, the conflict may be explained away as the rare case where the patient is not suffering from bronchitis given the symptoms and risk factors (similarly for Cancer). In general, if the normalized likelihood is greater than the conflict, then we may have a rare case.

The above method for detecting conflicts may fail. This will happen if the assumption of positively correlated pieces of evidence does not hold. The above approach can be combined with other methods such as those reported in Kim & Valtorta (1995) and Laskey (1991). These methods are based on using a more complex straw model for the comparison (i.e., evidence variables are not assumed independent) and a different measure to detect conflicts. The advantage of the above approach is that is computationally efficient.

The above method for detecting conflicts was introduced by Andersen et al. (1989) and the method is described in Jensen (1996) and Jensen (2001).

## 9.2 Hypothesis Driven Conflict Analysis

In hypothesis driven conflict analysis the impact of a finding on the probability of a hypothesis is investigated. In order to be able to relate the impacts of different findings on the probability of the hypothesis given evidence a measure is needed. This will allow us to identify pieces of evidence that conflict with the impact of the entire set of evidence.

### 9.2.1 Cost-of-Omission Measure

The main purpose of hypothesis driven conflict analysis is to identify pieces of evidence with an impact on the evidence that conflicts with the impact of the entire set of evidence. In order to perform this investigation a measure providing a numerical value specifying the *cost* of omitting a single piece of evidence is required. The *cost-of-omission*  $c(P(X|\varepsilon), P(X|\varepsilon \setminus \{\varepsilon_i\}))$  of  $\varepsilon_i$  is defined as

$$c(P(X|\varepsilon), P(X|\varepsilon \setminus \{\varepsilon_i\})) = \sum_{x \in \text{dom}(X)} P(x|\varepsilon) \log \frac{P(x|\varepsilon)}{P(x|\varepsilon \setminus \{\varepsilon_i\})}. \quad (9.1)$$

The above equation is undefined for values  $P(x|\varepsilon) = 0$  and  $P(x|\varepsilon \setminus \{\varepsilon_i\}) = 0$ . For these two cases, we define cost-of-omission to be 0 and infinity, respectively.

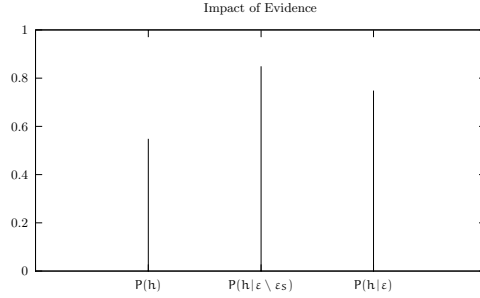
### 9.2.2 Evidence with Conflict Impact

Let  $H$  be a hypothesis variable with states  $\text{dom}(H) = \{h_1, \dots, h_n\}$  and let  $\varepsilon = \{\varepsilon_1, \dots, \varepsilon_m\}$  be the set of evidence. The *impact* of a finding  $\varepsilon_i \in \varepsilon$  on a hypothesis  $h \in \text{dom}(H)$  is determined by computing and comparing the prior probability of the hypothesis  $P(h)$ , the posterior probability of the hypothesis given all evidence  $P(h|\varepsilon)$ , and the posterior probability of the hypothesis given all evidence except the finding under consideration  $P(h|\varepsilon \setminus \varepsilon_i)$ . By comparing these three probabilities we can identify findings that have a conflicting impact on the probability of the hypothesis compared with the impact of the entire set of evidence.

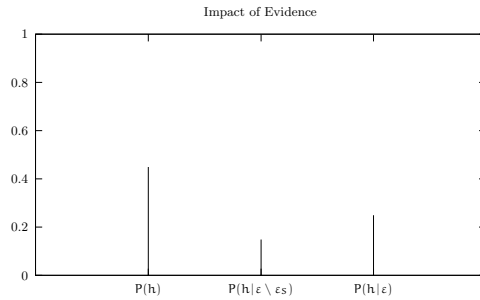
*Example 9.6 (Asia).* In the Asia example we assume evidence  $\varepsilon = \{\text{Dyspnoea} = \text{no}, \text{Smoker} = \text{yes}, \text{X\_ray} = \text{no}\} = \{\varepsilon_D, \varepsilon_S, \varepsilon_X\}$ . Assume further that  $B = \text{Bronchitis}$  is the hypothesis variable under consideration.

Figure 9.2 shows the impact of the finding  $\varepsilon_S$  on the hypothesis  $B = \text{no}$  while Figure 9.3 shows the impact of the finding  $\varepsilon_S$  on the hypothesis  $B = \text{yes}$ . From Figure 9.2 it is clear that the finding  $\varepsilon_S$  acts against the hypothesis  $B = \text{no}$ . The probability of the hypothesis is higher when the finding  $\varepsilon_S$  is excluded than when it is included. The posterior is higher than the prior. This implies that the combined effect of the evidence acts in favor of the hypothesis.

Similarly, from Figure 9.3 it is clear that the finding  $\varepsilon_S$  acts in favor of the hypothesis  $B = \text{yes}$ . The probability of the hypothesis is higher when the



**Fig. 9.2.** The impact of finding  $\varepsilon_S$  on the hypothesis  $h : B = \text{no}$ .



**Fig. 9.3.** The impact of finding  $\varepsilon_S$  on the hypothesis  $h : B = \text{yes}$ .

finding  $\varepsilon_S$  is included than when it is excluded, but not as high as the prior though. The posterior is lower than the prior. This implies that the combined effect of the evidence acts against the hypothesis.

The numbers in the two graphs are pairwise complementary since  $B$  is binary.

When considering the impact of findings given a large set of evidence it may be an advantage to use a cost-of-omission threshold to focus on findings with a cost-of-omission greater than the threshold.

*Example 9.7.* In Example 9.6 the cost-of-omission of finding  $\varepsilon_S$  is 0.03, i.e.,

$$c(P(B|\varepsilon), P(B|\varepsilon \setminus \{\varepsilon_S\})) = 0.03.$$

Further information on hypothesis driven conflict analysis can be found in Suermondt (1992).

### 9.3 Summary

In this chapter we have considered evidence and hypothesis driven conflict analysis in Bayesian networks.

The objective of evidence driven conflict analysis is to detect possible conflicts in the evidence. To support this analysis, we have defined a conflict measure that is simple to compute. The conflict measure is computed based on an alternative and much simpler model (the straw model). The conflict measure is defined such that a positive value is an indication that a conflict may be present in the evidence. Once a possible conflict is detected, we try to trace and resolve the conflict. We say that a hypothesis may resolve the conflict if the log of the normalized likelihood of the hypothesis is greater than the conflict. Furthermore, a positive conflict measure may originate from a rare case.

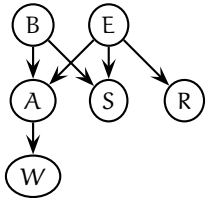
The objective of hypothesis driven conflict analysis is to investigate the impact of a single piece of evidence on the probability of a hypothesis compared with the impact of all the evidence. To support this investigation, we have defined a cost-of-omission measure. The cost-of-omission measure is used to measure the difference between including and excluding the selected piece of evidence on the probability of the hypothesis given evidence. In hypothesis driven conflict analysis we relate the prior probability of the hypothesis to the probability of the hypothesis given the entire set of evidence, and the probability of the hypothesis given the entire set of evidence except the selected piece of evidence. This enables us to determine whether or not a single piece of evidence conflicts with the remaining set of evidence with respect to the probability of the hypothesis.

In Chapter 10 we consider sensitivity analysis. Evidence sensitivity analysis is to determine the sensitivity of the posterior probability of a hypothesis relative to observations made. Parameter sensitivity is to determine the sensitivity of the posterior probability of a hypothesis relative to parameters of the model.

### Exercises

**Exercise 9.1.** From Example 2.4 on page 25, we know that Dr Watson makes frequent calls to Mr Holmes regarding the burglar alarm, however, till now the cause of activation of the alarm has been small earthquakes or a big truck passing by near the house. Every time Mr Holmes rushes home, just to find that everything is in order; so now Mr Holmes is installing a seismometer in his house with a direct line to his office. In this exercise we assume  $P(B) = P(E) = (0.1, 0.9)$ .

The revised model in Figure 9.4 captures the situation where Mr Holmes has installed a seismometer in his house with a direct line to the office. Assume  $S$  has states reflecting **no**, **some** and **large** vibrations in the house. The conditional probability distribution  $P(S|B, E)$  is shown in Table 9.2.



**Fig. 9.4.** Mr Holmes installs a seismometer with a direct line to his office.

B	E	S		
		no	some	large
no	no	0.97	0.02	0.01
no	yes	0.01	0.97	0.02
yes	no	0.01	0.02	0.97
yes	yes	0	0.03	0.97

**Table 9.2.** The conditional probability distribution  $P(S|B, E)$ .

- (a) One afternoon Dr Watson calls again and announces that Mr Holmes’ alarm has gone off. Mr Holmes checks the seismometer, it is in state **no**. Are the two observations in conflict?
- (b) Mr Holmes looks out his window. It rains heavily. When it rains heavily a flood is likely to occur. Extend the model in Figure 9.4 to capture these events when the prior of rain is 0.01 and rain causes a flood in one out of ten cases. The conditional probability table  $P(A|B, E, F)$  where F represents flood is shown in Table 9.3.

E	B	F	A	
			no	yes
no	no	no	0.99	0.01
no	no	yes	0.01	0.99
no	yes	no	0.01	0.99
no	yes	yes	0	1
yes	no	no	0.01	0.99
yes	no	yes	0	1
yes	yes	no	0	1
yes	yes	yes	0	1

**Table 9.3.** The conditional probability distribution  $P(A|B, E, F)$ .

Are the observations in conflict in this model and what is the value of the conflict measure?

- (c) Is there a potential explanation of the value of the conflict measure?



- (d) What is the partial conflict of each subset of the observations and what conclusion can be derived from the partial conflicts?

**Exercise 9.2.** Consider again the model with a seismometer of Mr Holmes in Exercise 9.1.

- (a) Perform hypothesis driven conflict analyses with respect to both `Burglar = yes` and `Earthquake = yes`.  
(b) What is the cost-of-omission for  $\epsilon_R$  with respect to `Burglar` and `Earthquake`?

---

## Sensitivity Analysis

We construct probabilistic networks to support and solve problems of reasoning and decision making under uncertainty. In problems of reasoning under uncertainty the posterior probability of a single hypothesis variable is sometimes of interest. When the evidence set consists of a large number of findings or even when it consists of only a small number of findings questions concerning the impact of subsets of the evidence on the hypothesis or a competing hypothesis emerge.

Evidence sensitivity analysis may, for instance, give answers to questions like *what are the minimum and maximum beliefs produced by observing a variable, which evidence acts in favor of or against a hypothesis, which evidence discriminates one hypothesis from an alternative hypothesis, and what if a certain observed variable had been observed to a value different from the actual value?* Knowing the answers to these and similar questions may help to explain and understand the conclusions reached by the model as a result of probabilistic inference. It will also help to understand the impact of subsets of the evidence on a certain hypothesis and alternative hypotheses.

Evidence sensitivity analysis is not the only possible kind of sensitivity analysis that can be performed on a probabilistic network. Parameter sensitivity analysis is another type of sensitivity analysis that is supported by probabilistic networks. We focus on parameter sensitivity analysis in discrete Bayesian networks. The parameters considered in parameter sensitivity analysis are the entries of the conditional probability distributions specified in the Bayesian network. The analysis is performed relative to a hypothesis and a given set of evidence. It has been shown that there is a (surprisingly) simple correlation between the probability of a set of evidence and an entry of a conditional probability distribution. The probability of the evidence is a linear function of the parameter. This knowledge can be exploited to determine the functional relation between the probability of a hypothesis given a subset of evidence and a parameter of a conditional probability distribution.

Parameter sensitivity analysis is particularly useful for identifying parameters of a probabilistic network that have a large or small impact on the

probability of a hypothesis given evidence. When knowledge elicitation resources are limited, parameter sensitivity analysis is a useful tool for identifying and focusing resources on the parameters that are most influential on the posterior probability of a hypothesis given evidence. That is, parameter sensitivity analysis can be used in an attempt to focus knowledge elicitation resources in the model construction process.

In Section 10.1, we introduce evidence sensitivity analysis. A distance measure designed to measure the impact of evidence on the probability of a hypothesis is introduced. In the following subsections we consider identifying minimum and maximum beliefs in a hypothesis given various subsets of the evidence, the impact of different evidence subsets on a hypothesis, how subsets of the evidence discriminates between a pair of competing hypotheses, what-if analysis, and the impact of findings on a hypothesis variable. In Section 10.2 parameter sensitivity analysis is introduced.

## 10.1 Evidence Sensitivity Analysis

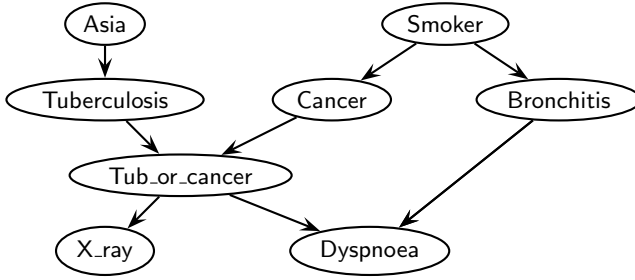
Evidence sensitivity analysis (SE analysis) is the analysis of how sensitive the results of a belief update (propagation of evidence) is to variations in the set of evidence (observations, likelihood, etc.).

Consider the situation where a decision maker has to make a decision based on the probability distribution of a hypothesis variable. It could, for instance, be a physician deciding on a treatment of a patient given the probability distribution of a disease variable. Prior to deciding on a treatment the physician may have the option to investigate the impact of the collected information on the posterior distribution of the hypothesis variable. That is, given a set of findings and a hypothesis, which sets of findings are in favor of, against, or irrelevant for the hypothesis, which sets of findings discriminate the hypothesis from an alternative hypothesis, what if a variable had been observed to a different value than the one observed, etc. These questions can be answered by SE analysis.

Given a Bayesian network model and a hypothesis variable, the task is to determine how sensitive the belief in the hypothesis variable is to variations in the evidence. We consider one-step look-ahead hypothesis driven SE analysis on discrete random variables.

*Example 10.1 (Asia).* As an example we consider SE analysis on the Asia example shown in Figure 10.1 (see Example 4.2 on page 69 for more details). The hypothesis variable is Bronchitis (B) and the initial set of evidence is  $\varepsilon = \{\varepsilon_S, \varepsilon_D\} = \{S = \text{no}, D = \text{yes}\}$ . That is, we are considering whether or not the patient is suffering from bronchitis after observing that the patient does not smoke (Smoker = no), but has shortness of breath (Dyspnoea = yes).

This example is used in the following sections to illustrate concepts of SE analysis.



**Fig. 10.1.** A graph specifying the independence and dependence relations of the Asia example.

### 10.1.1 Distance and Cost-of-Omission Measures

The main purpose of hypothesis driven SE analysis is to investigate how changes in the set of evidence impact the probability of a hypothesis. In order to perform this investigation, two distance measures are required. Each distance measure will provide a numerical value specifying the *distance* between either two probabilities or two probability distributions.

Let  $X$  be a hypothesis variable with state space  $\text{dom}(X) = \{x_1, \dots, x_n\}$  and let  $\varepsilon = \{\varepsilon_1, \dots, \varepsilon_m\}$  be a set of evidence (findings). We let  $\varepsilon_Y \in \varepsilon$  denote the finding on variable  $Y \in \mathcal{X}(\varepsilon)$ .

The distance  $d(p, q)$  between two probabilities  $p$  and  $q$  is defined, for  $p \neq 0$ , as

$$d(p, q) = \left| \frac{q}{p} - 1 \right|.$$

This measure is, for instance, useful for measuring the distance between the probability  $P(x|\varepsilon)$  of hypothesis  $x$  given evidence  $\varepsilon$  and the probability  $P(x|\varepsilon \setminus \{\varepsilon_i\})$  of hypothesis  $x$  given evidence  $\varepsilon \setminus \{\varepsilon_i\}$ ; i.e., the set of evidence where  $\varepsilon_i$  is excluded from  $\varepsilon$ .

A pair of probabilities  $p$  and  $q$  are said to be *almost equal* when their distance  $d(p, q)$  is below a predefined threshold  $\delta$ ; i.e.,  $d(p, q) < \delta$ .

The *cost-of-omission*  $c(P(X|\varepsilon), P(X|\varepsilon \setminus \{\varepsilon_i\}))$  of  $\varepsilon_i$  was defined in Section 9.2.1 on page 267 as:

$$c(P(X|\varepsilon), P(X|\varepsilon \setminus \{\varepsilon_i\})) = \sum_{x \in \text{dom}(X)} P(x|\varepsilon) \log \left( \frac{P(x|\varepsilon)}{P(x|\varepsilon \setminus \{\varepsilon_i\})} \right).$$

Notice the difference between the distance measure and the cost-of-omission measure. The distance measure evaluates the distance between probability values whereas the cost-of-omission measure evaluates the distance between two posterior probability distributions relative to omitting a certain finding  $\varepsilon_i$  from the evidence  $\varepsilon$ . The cost-of-omission measure is a special

case of the more general cross entropy distance (or Kullback–Leibler distance) measure between a probability distribution  $P$  and an approximation  $P'$  of  $P$ :

$$H(P, P') = \sum_{x \in \text{dom}(X)} P(x) \log \left( \frac{P(x)}{P'(x)} \right).$$

The cost-of-omission measure is, for instance, useful for measuring the distance between the posterior probability distribution  $P(X|\varepsilon)$  of hypothesis variable  $X$  given evidence  $\varepsilon$  and the posterior probability distribution  $P(X|\varepsilon \setminus \{\varepsilon_i\})$  of hypothesis variable  $X$  given evidence  $\varepsilon \setminus \{\varepsilon_i\}$ ; i.e., the set of evidence where  $\varepsilon_i$  is excluded from  $\varepsilon$ .

In the following sections, the distance measures defined above are used to introduce different concepts related to SE analysis.

### 10.1.2 Identify Minimum and Maximum Beliefs

As part of performing SE analysis we may be interested in knowing the minimum and maximum values of the posterior belief for each possible state  $x \in \text{dom}(X)$  of the hypothesis variable  $X$  given all possible observations on a given variable  $Y \notin \mathcal{X}(\varepsilon)$ ; i.e., what are the minimum and maximum values of  $P(x|\varepsilon, y)$  as a function of  $y \in \text{dom}(Y)$ .

The minimum  $\min_{y \in \text{dom}(Y)} P(x|\varepsilon, y)$  and maximum  $\max_{y \in \text{dom}(Y)} P(x|\varepsilon, y)$  values of the posterior belief are determined by entering and propagating each state  $y$  of the information variable  $Y$ . This analysis requires one belief update for each state of variable  $Y$ .

This analysis identifies the range of the posterior belief in a hypothesis as a function of possible observations on an unobserved variable. This may help to determine the impact of a possible observation on the probability of the hypothesis.

*Example 10.2 (Example 10.1 continued).* Table 10.1 shows the sensitivity of the posterior probability distribution  $P(B|\varepsilon, a)$  of the hypothesis variable  $B$  relative to instantiations of the unobserved variable  $Asia$  ( $A$ ).

$b$	$\min_a P(B = b \varepsilon, a)$	$P(B = b \varepsilon)$	$\max_a P(B = b \varepsilon, a)$
no	0.228	0.228	0.236
yes	0.764	0.772	0.772

**Table 10.1.** Sensitivity of the posterior probability distribution of the hypothesis variable  $B$  to findings on  $A$ .

For each state  $b \in \text{dom}(B)$  of  $B$  the minimum posterior belief  $\min_a P(B = b|\varepsilon, a)$ , the current belief  $P(B = b|\varepsilon)$ , and the maximum posterior belief  $\max_a P(B = b|\varepsilon, a)$  is shown. From the table it is clear that an observation

on  $A$  would produce insignificant variations in the posterior belief in any state of  $B$ .

### 10.1.3 Impact of Evidence Subsets

Investigation of the impact of different subsets of the evidence  $\varepsilon$  on each state  $x \in \text{dom}(X)$  of the hypothesis variable  $X$  is a useful part of SE analysis. Investigating the impact of different subsets of the evidence on states of the hypothesis may help to determine subsets of the evidence acting in favor of or against each possible hypothesis.

The impact of a subset of the evidence  $\varepsilon' \subseteq \varepsilon$  on a state  $x$  of the hypothesis variable  $X$  is determined by computing the *normalized likelihood*  $NL$  of the hypothesis  $x$  given evidence  $\varepsilon'$ ; i.e.,

$$NL = \frac{P(\varepsilon' | x)}{P(\varepsilon')} = \frac{P(\varepsilon', x) / P(x)}{P(\varepsilon')} = \frac{P(x | \varepsilon') P(\varepsilon') / P(x)}{P(\varepsilon')} = \frac{P(x | \varepsilon')}{P(x)},$$

where we assume  $P(\varepsilon') > 0$  and  $P(x) > 0$ . This fraction is computed by entering and propagating  $\varepsilon'$ . Therefore, this analysis requires one belief update for each subset  $\varepsilon'$  of the evidence  $\varepsilon$ .

Each normalized likelihood is a measure of the impact of a subset of evidence on the hypothesis. By comparing the normalized likelihoods of different subsets of the evidence, we compare the impacts of the subsets of evidence on the hypothesis.

*Example 10.3 (Example 10.2 continued).* Assume that we observe the patient to have a positive X-ray result  $X = \text{yes}$ , such that the set of evidence is  $\varepsilon = \{\varepsilon_S, \varepsilon_D, \varepsilon_X\} = \{S = \text{no}, D = \text{yes}, X = \text{yes}\}$ . Table 10.2 shows the normalized likelihood of the hypothesis  $h_B : B = \text{yes}$  given the evidence  $\varepsilon = \{\varepsilon_S, \varepsilon_D, \varepsilon_X\}$ .

$\varepsilon'$			NL
$\varepsilon_S$	$\varepsilon_X$	$\varepsilon_D$	1.256
$\varepsilon_S$	$\varepsilon_X$	—	0.667
$\varepsilon_S$	—	$\varepsilon_D$	1.675
$\varepsilon_S$	—	—	0.667
—	$\varepsilon_X$	$\varepsilon_D$	1.515
—	$\varepsilon_X$	—	1.125
—	—	$\varepsilon_D$	1.853
—	—	—	1

**Table 10.2.** Normalized likelihood of hypothesis  $h_B$  given all subsets of the evidence  $\varepsilon$ .

From Table 10.2 it is clear that the finding  $\varepsilon_D$  on  $D$  acts in favor of the hypothesis  $h_B$ . On the other hand, the evidence  $\varepsilon_S$  acts slightly against the

hypothesis  $h_B$  while  $\varepsilon_X$  is irrelevant, against and in favor of  $h_B$  depending on the remaining evidence.

### 10.1.4 Discrimination of Competing Hypotheses

A central question considered by SE analysis is how different subsets of the evidence discriminate between competing hypotheses. The challenge is to compare the impact of subsets of the evidence on competing hypotheses.

We consider the discrimination between two different hypotheses represented as states of two different variables. Thus, let  $X$  be the hypothesis variable of interest and let  $Y$  be an alternative hypothesis variable where  $X \neq Y$ .

In Section 3.5, we describe how the discrimination of a pair of competing hypotheses  $x \in \text{dom}(X)$  and  $y \in \text{dom}(Y)$  may be based on the calculation of *Bayes' factor*  $B$  (or *Bayesian likelihood ratio*) for all subsets  $\varepsilon' \subseteq \varepsilon$  of a set of evidence  $\varepsilon$ :

$$B = \frac{\text{posterior odds ratio}}{\text{prior odds ratio}} = \frac{P(x|\varepsilon')/P(y|\varepsilon')}{P(x)/P(y)} = \frac{P(\varepsilon'|x)}{P(\varepsilon'|y)} = \frac{L(x|\varepsilon')}{L(y|\varepsilon')}, \quad (10.1)$$

where we assume  $P(x) > 0$ ,  $P(y) > 0$ , and  $P(\varepsilon') > 0$ . Bayes' factor is the ratio of the likelihoods of hypothesis  $x$  and  $y$  given the evidence  $\varepsilon'$ .

From Equation 10.1 we see that

- $B > 1$  if the evidence  $\varepsilon'$  provides more support for  $x$  than for  $y$ ,
- $B < 1$  if the evidence  $\varepsilon'$  provides less support for  $x$  than for  $y$ , and
- $B = 1$  if the evidence  $\varepsilon'$  does not provide useful information for differentiating between  $x$  and  $y$ .

This analysis requires one belief update for each subset  $\varepsilon' \subseteq \varepsilon$ .

*Example 10.4 (Example 10.3 continued).* Assume that  $h_L : \text{Cancer} = \text{yes}$  is an alternative hypothesis to the hypothesis  $h_B$ . Table 10.3 shows Bayes' factor for the hypothesis  $h_B$  and the alternative hypothesis  $h_L$ .

$\varepsilon'$			B
$\varepsilon_S$	$\varepsilon_X$	$\varepsilon_D$	0.281
$\varepsilon_S$	$\varepsilon_X$	—	0.258
$\varepsilon_S$	—	$\varepsilon_D$	3.869
$\varepsilon_S$	—	—	3.667
—	$\varepsilon_X$	$\varepsilon_D$	0.134
—	$\varepsilon_X$	—	0.127
—	—	$\varepsilon_D$	0.992
—	—	—	1

**Table 10.3.** Discrimination between hypothesis  $h_B$  and the alternative hypothesis  $h_L$ .

From Table 10.3 it is clear that subsets  $\{\varepsilon_S\}$  and  $\{\varepsilon_S, \varepsilon_D\}$  acts in favor of the hypothesis  $h_B$  when compared with the alternative hypothesis  $h_L$ . On the other hand, the remaining subsets act slightly against the hypothesis  $h_B$  when compared with the alternative hypothesis  $h_L$ .

### 10.1.5 What-If Analysis

In *what-if* analysis the type of question considered is the following. What if the finding on a discrete random variable  $Y \in \mathcal{X}(\varepsilon)$  had been the observation  $Y = y'$  instead of  $Y = y$  (represented by the finding  $\varepsilon_Y \in \varepsilon$ , where  $\varepsilon$  is the set of evidence)? We consider a hypothesis driven approach to what-if SE analysis.

Hypothesis driven what-if analysis is performed by computing the posterior probability distribution  $P(X|\varepsilon \setminus \{\varepsilon_Y\}, y')$  of the hypothesis variable  $X$  for each possible state  $y' \neq y$  of the observed variable  $Y$ .

The posterior probability distribution  $P(X|\varepsilon \setminus \{\varepsilon_Y\}, y')$  specifies the impact of each possible instantiation of  $Y$  on the posterior distribution of the hypothesis variable  $X$ . The analysis requires one belief update for each  $y' \in \text{dom}(Y)$ . Notice that  $\varepsilon_Y$  need not be an instantiation of  $Y$ ; i.e.,  $\varepsilon_Y$  may be soft evidence.

*Example 10.5 (Example 10.4 continued).* For each finding variable  $Y$  we may consider the impact of each possible observation  $Y = y$ . Table 10.4 shows the posterior belief in the hypothesis  $B = \text{yes}$  given the evidence where the finding  $y$  is substituted with each possible state  $y' \in \text{dom}(Y)$ .

Y	y'	$P(B = \text{yes} \varepsilon \setminus \{\varepsilon_Y\}, y')$
D	no	0.092
D	yes	0.565
S	no	0.565
S	yes	0.714
X	no	0.774
X	yes	0.565

**Table 10.4.** What-if analysis on findings.

From Table 10.4 it is clear that changing the observation on  $D$  from **yes** to **no** has a significant impact of the posterior belief in the hypothesis  $B = \text{yes}$ . On the other hand, the posterior belief in the hypothesis  $B = \text{yes}$  has a lower sensitivity to observations on  $S$  and  $X$ .

Since each finding (i.e.,  $\varepsilon_S$ ,  $\varepsilon_X$ , or  $\varepsilon_D$ ) is an instantiation, one row for each observed variable  $Y$  corresponds to the posterior belief in the hypothesis  $B = \text{yes}$ . That is,  $P(B = \text{yes}|\varepsilon) = 0.565$  is represented three times in the table.



### 10.1.6 Impact of Findings

Let  $X = x$  be the hypothesis of interest where  $X$  is the hypothesis variable and let  $\varepsilon$  be the entire set of evidence. The impact of each finding  $\varepsilon_Y \in \varepsilon$  on the probability of  $x$  is determined by computing and comparing the prior probability of the hypothesis,  $P(x)$ , the posterior probability of the hypothesis given the entire set of evidence,  $P(x|\varepsilon)$ , and the posterior probability of the hypothesis given the entire set of evidence except the finding  $\varepsilon_Y$ ,  $P(x|\varepsilon \setminus \{\varepsilon_Y\})$ .

To relate the impact of individual findings on the probability of the hypothesis we define the notions of an important finding, a redundant finding, and an irrelevant finding:

- A finding  $\varepsilon_Y \in \varepsilon$  is *important* when the difference between the probability  $q = P(x|\varepsilon \setminus \{\varepsilon_Y\})$  of the hypothesis given the entire set of evidence except  $\varepsilon_Y$  and the probability  $p = P(x|\varepsilon)$  of the hypothesis given the entire set of evidence is *too large*; i.e., the probabilities  $p$  and  $q$  are not *almost equal* ( $d(p, q) \geq \delta$ ).
- A finding  $\varepsilon_Y \in \varepsilon$  is *redundant* when  $q = P(x|\varepsilon \setminus \{\varepsilon_Y\})$  is *almost equal* to  $p = P(x|\varepsilon)$ ; i.e.,  $d(p, q) < \delta$ .
- A finding  $\varepsilon_Y \in \varepsilon$  is *irrelevant* when  $q = P(x|\varepsilon' \setminus \{\varepsilon_Y\})$  is *almost equal* to  $p = P(x|\varepsilon')$  for all subsets  $\varepsilon'$ ; i.e.,  $d(p, q) < \delta$  for all subsets  $\varepsilon'$ . That is, the finding  $\varepsilon_Y$  is redundant for all subsets of the evidence.

The term *almost equal* is defined based on the distance measure introduced in Section 10.1.1. Similarly, a sufficient set of evidence is defined as:

- A subset of evidence  $\varepsilon' \subseteq \varepsilon$ , e.g., the entire set of evidence  $\varepsilon$  except a certain finding  $\varepsilon_Y$ , is *sufficient* when  $q = P(x|\varepsilon')$  is *almost equal* to  $p = P(x|\varepsilon)$ ; i.e.,  $d(p, q) < \delta$ .

The impact of each finding  $\varepsilon_Y$  may be considered for each state or a certain state of the hypothesis variable  $X$ . Sufficiency  $\delta_s$  and importance  $\delta_i$  thresholds should be specified by the user.

*Example 10.6 (Example 10.5 continued).* We may be interested in considering the impact of each finding  $\varepsilon_Y \in \varepsilon$  on the probability of the hypothesis  $B = \text{yes}$  by comparing  $P(B = \text{yes})$ ,  $P(B = \text{yes}|\varepsilon)$ , and  $P(B = \text{yes}|\varepsilon \setminus \{\varepsilon_Y\})$ . Table 10.5 shows the prior belief in the hypothesis  $B = \text{yes}$ , the posterior belief given all evidence  $P(B = \text{yes}|\varepsilon)$ , and the posterior belief given all evidence except a single finding  $P(B = \text{yes}|\varepsilon \setminus \{\varepsilon_Y\})$ .

From Table 10.5 we make the following observations:

- The finding  $\varepsilon_S$  is important. At sufficiency threshold  $\delta_s = 0.02$  the finding  $\varepsilon_S$  is redundant and  $\varepsilon \setminus \{\varepsilon_S\}$  is sufficient. At cost-of-omission threshold  $\delta_o = 0.03$  the evidence  $\varepsilon_S$  would not be included in the analysis.
- The finding  $\varepsilon_X$  is important.
- The finding  $\varepsilon_D$  is important.

$\varepsilon_Y$	$P(B = \text{yes})$	$P(B = \text{yes}   \varepsilon \setminus \{\varepsilon_Y\})$	$P(B = \text{yes}   \varepsilon)$
$\varepsilon_S$	0.45	0.682	0.565
$\varepsilon_X$	0.45	0.754	0.565
$\varepsilon_D$	0.45	0.3	0.565

**Table 10.5.** Findings impact analysis.

$\varepsilon_Y$	$c(P(B   \varepsilon), P(B   \varepsilon \setminus \{\varepsilon_Y\}))$	$d(P(B = \text{yes}   \varepsilon), P(B = \text{yes}   \varepsilon \setminus \{\varepsilon_Y\}))$
$\varepsilon_S$	0.03	0.171
$\varepsilon_X$	0.085	0.25
$\varepsilon_D$	0.151	0.884

**Table 10.6.** Cost-of-omission and distance in posterior beliefs of the hypothesis for each finding.

The subset  $\varepsilon' = \{\varepsilon_S, \varepsilon_X, \varepsilon_D\} = \varepsilon$  is, of course, also sufficient. The analysis is performed using threshold values  $\delta_o = 0.0001$ ,  $\delta_s = 0.02$ , and  $\delta_i = 0.05$ . Table 10.6 shows the cost-of-omission  $c(P(B | \varepsilon), P(B | \varepsilon \setminus \{\varepsilon_Y\}))$  and the distance  $d(P(B = \text{yes} | \varepsilon), P(B = \text{yes} | \varepsilon \setminus \{\varepsilon_Y\}))$  for each finding  $\varepsilon_Y$ .

## 10.2 Parameter Sensitivity Analysis

Parameter sensitivity analysis (SP analysis) is the analysis of how sensitive the results of a belief update (propagation of evidence) is to variations in the value of a parameter of the model. The parameters of a model are the entries of the conditional probability distributions.

Consider the situation where company management allocates resources to research and development projects based on an estimation of projects' successes. The success of a project depends on the ability of the project management to obtain certain environmental permissions from the authorities. This and other properties of the domain are modeled as a Bayesian network. As part of the model construction the knowledge engineers (and the management of the company) would like to assess how sensitive the conclusion of the model (i.e., the probability of project success) is to the prior probability of a specific environmental permission being obtained. Parameter sensitivity analysis is designed to answer such questions. Given a Bayesian network model, a hypothesis and a set of evidence, the task is to determine the sensitivity of the posterior belief in the hypothesis to variations in the value of an assessed parameter.

We consider scenario-based SP analysis on discrete random variables with respect to changes in a single parameter value where a scenario  $S$  is defined as a vector consisting of a hypothesis variable  $H$ , a state of the hypothesis variable  $h$  and a set of evidence  $\varepsilon$ , i.e.,  $S = (H, h, \varepsilon)$ .

*Example 10.7 (Apple Jack).* Apple Jack, see Example 4.1 on page 66, is interested in computing the probability of his finest apple tree being sick. His hypothesis is that the tree is sick, i.e., the hypothesis is  $\text{Sick} = \text{yes}$ . The evidence available to support the reasoning of Apple Jack is that the tree is losing its leaves. Thus, the scenario under consideration is  $S = (\text{Sick}, \text{yes}, \{\text{Loses} = \text{yes}\})$ . Given the Bayesian network shown in Figure 4.1 on page 66 and the conditional probability distributions  $P(\text{Sick}) = (0.95, 0.05)$ ,  $P(\text{Dry}) = (0.9, 0.1)$  and  $P(\text{Loses}|\text{Sick}, \text{Dry})$  as specified in Table 4.1 on page 67, the posterior distribution of the hypothesis given the observation,  $P(\text{Sick} = \text{yes}|\varepsilon)$ , is 31.62%.

How sensitive is this posterior probability to small variations in the quantification of the model? For instance, how would the posterior probability of the hypothesis change if the prior probability of  $\text{Dry} = \text{yes}$  decreases from 0.1 to 0.075? Setting the prior probability of  $\text{Dry} = \text{yes}$  to 0.075, the posterior distribution of the hypothesis given the observation,  $P(\text{Sick} = \text{yes}|\varepsilon)$ , is 36.64%.

This shows that the posterior probability of the hypothesis  $\text{Sick} = \text{yes}$  (and other events) changes when the prior on  $\text{Dry} = \text{yes}$  is changed to 0.075 (from 0.1). The posterior probability of  $\text{Sick} = \text{yes}$  increases from 31.52% to 36.64%. This seems intuitive as the prior of one cause decreases and the posterior of another cause increases given the observed effect. However, what if the prior had been changed to a different value? Is it necessary to compute the posterior probability of the hypothesis for all possible values of  $P(\text{Dry} = \text{yes})$ , i.e., the parameter we are investigating?

The aforementioned questions may be answered more efficiently using parameter sensitivity analysis.

### 10.2.1 Sensitivity Function

Parameter sensitivity analysis is based on the observation that the probability of the evidence is a linear function of any single parameter in the model; i.e., any entry of any conditional probability distribution (Castillo, Gutiérrez & Hadi 1997, Coupé & van der Gaag 1998). That is,  $y = P(\varepsilon)$  as a function of a conditional probability  $t = P(X = x | \text{pa}(X) = z)$  has the simple form  $y = \alpha \cdot t + \beta$  where  $\alpha, \beta \in \mathbb{R}$ . This implies that the conditional probability of a hypothesis  $h$  given evidence  $\varepsilon$  as a function of a parameter  $t$  has the form

$$f(t) = P(h|\varepsilon)(t) = \frac{P(h, \varepsilon)(t)}{P(\varepsilon)(t)} = \frac{\alpha \cdot t + \beta}{\gamma \cdot t + \delta},$$

where  $\alpha, \beta, \gamma, \delta \in \mathbb{R}$ . Hence, the posterior probability  $P(h|\varepsilon)$  is a quotient of two linear functions of the parameter  $t$ .

The function  $f(t)$  is known as the *sensitivity function*. The coefficients of the sensitivity function are determined separately for its numerator and denominator functions. The coefficients of a linear function can be determined from two values of the function for two different values of the parameter. We can compute the value of the function for two different values of the parameter by propagating the evidence twice (once for each of the two parameter

values). When determining the coefficients of the sensitivity function, we use proportional scaling to change the remaining related parameters such that they keep the original proportion. This implies that when we change the parameter value for  $t$ , the remaining probability values for the corresponding parent configuration (i.e.,  $P(X = x' | pa(X) = z)$  for all  $x \neq x'$ ) are scaled proportionally. We need to scale the values such that the values sum to one; i.e.,  $\sum_x P(x | pa(X)) = 1$ . Assume  $P(X = x' | pa(X) = z) = (p_1, \dots, p_n)$  is the initial assessment of the probability of  $X$  given  $pa(X) = z$  and  $p_i$  is the parameter value under consideration. Proportional scaling on  $p_j$  for  $j \neq i$  when changing  $p_i$  to  $p_i^*$  amounts to computing

$$p_j^* = \frac{p_j(1 - p_i^*)}{\sum_{j \neq i} p_j},$$

where  $(p_1^*, \dots, p_n^*)$  is the updated probability of  $X$  given  $pa(X) = z$ .

We assume that each parameter can be varied independently of other parameters and that each parameter is non-extreme, i.e., it can be varied in an open interval around its initial assessment.

*Example 10.8 (Proportional Scaling).* Let  $S = (\text{Dry}, \text{yes}, \{\text{Loses} = \text{yes}\})$  be the scenario under consideration. Assume that the variable **Dry** has three states **no**, **dry** and **very dry** with a prior distribution  $P(\text{Dry}) = (0.1, 0.6, 0.3)$ . If we want to investigate the impact of adjusting the parameter  $P(\text{Dry} = \text{yes}) = 0.1$  to 0.075, then it is necessary to adjust the values of the other two parameters such that all three adjusted parameters sum to one. This is achieved by proportional scaling such that the adjusted prior distribution is

$$\begin{aligned} P(\text{Dry}) &= (0.075, \frac{0.6 \cdot (1 - 0.075)}{0.6 + 0.3}, \frac{0.3 \cdot (1 - 0.075)}{0.6 + 0.3}) \\ &= (0.075, \frac{0.555}{0.9}, \frac{0.2775}{0.9}) \\ &= (0.075, 0.6167, 0.3083). \end{aligned}$$

When a variable has only two states a change in the value of one parameter must induce a similar (but opposite) change in the other parameter.

*Example 10.9 (Sensitivity Function).* Let  $S = (\text{Sick}, \text{yes}, \varepsilon = \{\text{Loses} = \text{yes}\})$  be the scenario under consideration. Hence, the hypothesis under investigation is **Sick** = **yes** while the parameter in focus is  $t = P(\text{Dry} = \text{yes})$ . The sensitivity function  $f(t)$  where  $t$  is the parameter for  $P(\text{Dry} = \text{yes})$  is

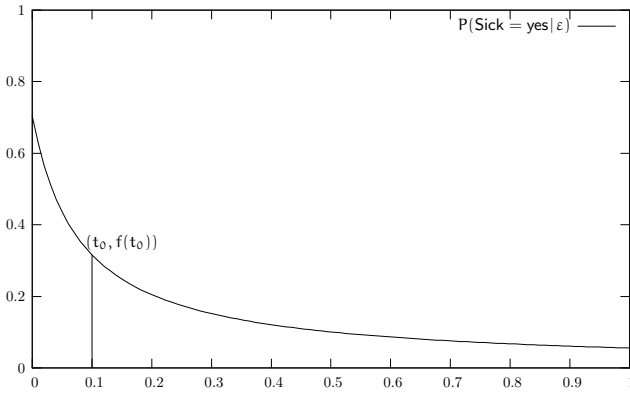
$$\begin{aligned} f(t) &= \frac{P(\text{Sick} = \text{yes} | \text{Loses} = \text{yes})}{P(\text{Loses} = \text{yes})} \\ &= \frac{\alpha \cdot t + \beta}{\gamma \cdot t + \delta} \\ &= \frac{0.0025 \cdot t + 0.045}{0.791 \cdot t + 0.064} \end{aligned}$$

The coefficients of denominator and numerator functions are determined separately. Both functions are linear in the parameter  $t$ . Thus, the coefficients of each function can be determined by propagating evidence for two different parameter values. For instance, the coefficients  $\gamma$  and  $\delta$  of the denominator can be determined as

$$\begin{aligned}\gamma &= \frac{P(\text{Loses} = \text{yes})(t_1) - P(\text{Loses} = \text{yes})(t_0)}{t_1 - t_0} = \frac{0.2222 - 0.1431}{0.2 - 0.1} = 0.791 \\ \delta &= P(\text{Loses} = \text{yes})(t_0) - \gamma \cdot t_0 = 0.1431 - 0.791 \cdot 0.1 = 0.064\end{aligned}$$

where  $t_0 = 0.1$  and  $t_1 = 0.2$  are two different values of the parameter  $t$ .

The graph of the sensitivity function  $f(t)$  for all possible values of  $t$ , i.e., values of  $t$  between zero and one, is plotted in Figure 10.2.



**Fig. 10.2.** The graph of the sensitivity function  $f(t) = P(\text{Sick} = \text{yes} | \text{Loses} = \text{yes})$  as a function of  $t = P(\text{Dry} = \text{yes})$ .

Figure 10.2 shows that the minimum value of the probability of the hypothesis is 0.0556 for  $t = 1$  while the maximum value of the probability of the hypothesis is 0.7031 for  $t = 0$ . Thus, no matter what value of  $t$  is specified  $P(\text{Sick} = \text{yes} | \epsilon)$  is between 0.0556 and 0.7031. In addition, it is clear from Figure 10.2 that the posterior probability of the hypothesis is more sensitive to small variations in the parameter value when the initial parameter value is in the range from 0 to, say, 0.25 than when the initial parameter is in the range from 0.25 to 1.

Performing two full propagations of the evidence for each parameter value may be inefficient if the number of parameters is large. Jensen (2001) describes a modeling technique for computing the coefficients of the linear function based on introducing an auxiliary variable (for each parameter inspected). By

introducing an auxiliary variable it is possible to reduce the number of messages to be passed in the junction tree representation. Madsen (2005) describes a propagation method that makes it possible to compute the coefficients for all parameters from a single propagation in a junction tree representation.

### 10.2.2 Sensitivity Value

The partial derivative  $f'(t) = \partial P(h|\epsilon)/\partial t$  of the sensitivity function  $f(t)$  with respect to  $t$  expresses how much  $P(h|\epsilon)(t)$  changes as a function of  $t$  given small variations in the initial assessment. The partial derivative  $f'(t)$  of the sensitivity function on  $t$  is

$$f'(t) = \frac{\alpha \cdot t + \beta}{(\gamma \cdot t + \delta)^2}.$$

The partial derivative reflects how the posterior probability of the hypothesis  $h$  changes with changes in the parameter  $t$  under evidence scenario  $\epsilon$ . Wang, Rish & Ma (2002) defines parameter sensitivity  $S(t|h, \epsilon)$  as  $f'(t) = \partial P(h|\epsilon)/\partial t$ . The sensitivity value of a parameter is defined as  $|S(t|h, \epsilon)|$ ; i.e., the absolute value of the derivative of the sensitivity function at the initial assessment of the parameter (Laskey 1993). The sign of  $S(t|h, \epsilon)$  indicates whether the probability of the hypothesis is increasing or decreasing in  $t$ .

The *sensitivity value* can be used as a guide to identify parameter assessments where small variations in the value may have the largest impact on the posterior probability of the hypothesis given the evidence. In general, a parameter is of interest when the sensitivity value is greater than zero. Parameter sensitivity analysis enables us to identify the most important parameter assessments in the Bayesian network. Let  $t'$  and  $t''$  be two parameters. If  $t'$  has a higher sensitivity value than  $t''$ , then  $t'$  will intuitively induce a larger change on the probability of interest than  $t''$  given the same variation in the parameter assessments.

When considering sensitivity analysis with respect to multiple evidence sets we may choose to weigh the parameter sensitivity with the probability of the evidence, i.e.,  $P(\epsilon) \cdot S(t|h, \epsilon)$  as different evidence scenarios may have different probabilities. Parameter importance defines the importance of a parameter across multiple evidence scenarios  $\epsilon$  and multiple hypotheses  $h$ . Wang et al. (2002) defines parameter importance  $I(t)$  as

$$I(t) = \frac{1}{mn} \sum_{h, \epsilon} S(t|h, \epsilon) = \frac{1}{mn} \sum_{h, \epsilon} \frac{\partial P(h|\epsilon)}{\partial t},$$

where  $m$  is the number of hypotheses and  $n$  is the number of evidence scenarios. The importance value of a parameter is defined as  $|I(t_0)|$ ; i.e., the absolute value of the parameter importance function at the initial assessment of the parameter.

*Example 10.10 (Sensitivity Value).* Let  $S = (\text{Dry}, \text{yes}, \{\text{Loses} = \text{yes}\})$  be the scenario under consideration. The initial value of the parameter of interest  $t = P(\text{Dry} = \text{yes})$  is  $t_0 = 0.1$ . This implies that the sensitivity value of the parameter  $t$  is  $f'(t_0) = 17$ .

On the other hand, the conditional probability  $P(\text{Loses} = \text{yes} | \text{Dry} = \text{yes}, \text{Sick} = \text{yes})$  has sensitivity function

$$f(t) = \frac{0.005 \cdot t + 0.13835}{0.005 \cdot t + 0.0405}.$$

The initial parameter assessment is  $t_0 = 0.95$  and the sensitivity value is 0.24.

### 10.2.3 Admissible Deviation

Parameter sensitivity values may be used to focus the knowledge elicitation resources in the model construction process. The sensitivity function, its derivative, and the sensitivity value are not sufficient tools for analyzing how the change in a parameter  $t$  may change the most likely state of a hypothesis variable  $H$ .

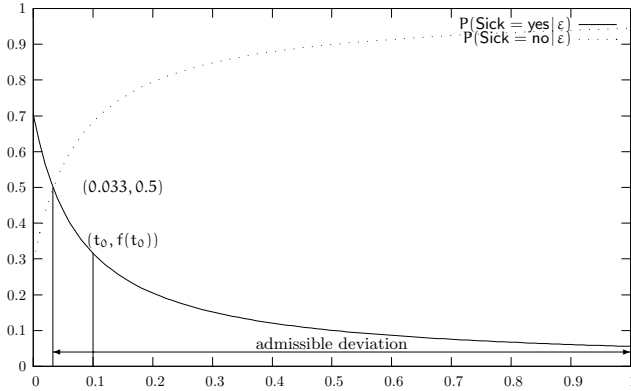
We extend the basic sensitivity analysis method with the calculation of an interval within which the parameter under investigation can be varied without changing the most likely value of the hypothesis variable of interest. Let  $H$  be the hypothesis variable of interest,  $\varepsilon$  the evidence scenario under consideration, and  $t$  the parameter under investigation with initial assessment  $t_0$ . The admissible deviation of  $t$  from  $t_0$  is a pair of real numbers  $(r, s)$  such that  $t$  can be varied from  $\min(0, t_0 - r)$  to  $\max(1, t_0 + s)$  without changing the most likely state of  $H$ , i.e.,  $\arg \max P(h | \varepsilon)$  is unchanged by the deviation of  $t$  from  $t_0$ . The values of  $(r, s)$  should be the largest such numbers for which the property is satisfied (Laskey 1993). The admissible deviation interval is  $[\min(0, t_0 - r); \max(1, t_0 + s)]$ . Notice that the interval specifying the admissible deviation is in general not symmetric around the value  $t_0$ , i.e., in general  $r$  is not equal to  $s$ .

Some parameters may take any value without changing the most likely state of  $H$ . This implies that the value of the parameter can be varied over the entire range  $[0; 1]$  without changing the most likely state of the hypothesis. In this case the admissible deviation interval is specified as  $(-\infty, \infty)$ .

*Example 10.11 (Admissible Deviation).* Assume that Apple Jack is interested in determining whether or not his apple tree is sick. The hypothesis variable of interest is *Sick*, the evidence scenario is *Loses = yes*, and the parameter under investigation is  $t = P(\text{Dry} = \text{yes})$ . How much can the parameter  $t$  be varied without inducing a change in the most likely state of *Sick*? Apple Jack wants to know the admissible deviation of  $t$ .

The sensitivity function  $f(t)$  for *Sick = no* is

$$f(t) = \frac{0.7885 \cdot t + 0.019}{0.791 \cdot t + 0.064}.$$



**Fig. 10.3.** The graph of the sensitivity functions for Sick = yes and Sick = no.

The sensitivity functions for Sick = no and Sick = yes are shown in Figure 10.3.

For  $t = 0.033$  we have  $P(\text{Sick} = \text{yes}|\varepsilon) = P(\text{Sick} = \text{no}|\varepsilon) = 0.5$ . Since the hypothesis variable Sick is binary, the two states have equal probability when they both have probability 0.5. Assuming that  $t_0 = 0.1$  the admissible deviation of  $t$  is the pair  $(0.0967, \infty)$ , i.e. the value of the parameter  $t$  can be varied from  $0.033 = 0.1 - 0.0967$  to 1 without changing the hypothesis with highest probability.

## 10.3 Summary

In this chapter we have considered evidence and parameter sensitivity analysis in Bayesian networks.

The objective of evidence sensitivity analysis is to investigate how sensitive the result of a belief update is to variations in the set of evidence. To support this analysis, we have defined two distance measures designed to provide a numerical value specifying the distance between either two probabilities or two probability distributions. Based on the distance measures, we have described five different types of evidence sensitivity analysis: identifying minimum and maximum beliefs, impact of evidence subsets, discrimination of competing hypotheses, what-if analysis, and impact of findings.

The objective of parameter sensitivity analysis is to investigate how sensitive the result of a belief update is to variations in a parameter of the model. It has been shown that there is a simple functional relation between the probability of a set of evidence and an entry of a conditional probability table; i.e., a parameter. The probability of the evidence is a simple linear function of the parameter. This insight may be used to perform parameter sensitivity



analysis on the posterior probability of a hypothesis given a set of evidence. Parameter sensitivity values may be used to focus the knowledge elicitation resources in the model construction process.

In Chapter 11 we consider value of information analysis. Value of information analysis is to compute the value of potential new observations.

Exercises

**Exercise 10.1.** In the morning when Mr Holmes leaves his house he realizes that his grass is wet. He wonders whether it has rained during the night or whether he has forgotten to turn off his sprinkler. He looks at the grass of his neighbors, Dr Watson and Mrs Gibbon. Both lawns are dry and he concludes that he must have forgotten to turn off his sprinkler. (This problem was also discussed in Exercise 6.3 on page 175.)

The structure of a network for modeling the above scenario is shown in Figure 10.4.

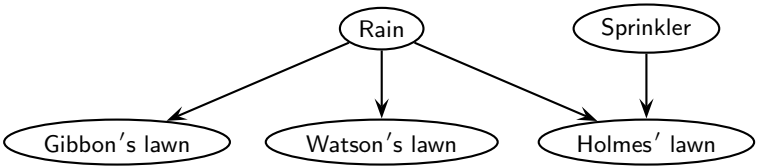


Fig. 10.4. The Wet Grass network.

Prior probability distributions are  $P(\text{Rain}) = P(\text{Sprinkler}) = (0.1, 0.9)$  while the conditional probability distributions are shown in Table 10.7 to Table 10.9.

Rain	Sprinkler	Holmes' lawn	
		dry	wet
no	no	1	0
no	yes	0.1	0.9
yes	no	0.01	0.99
yes	yes	0	1

**Table 10.7.** The conditional probability distribution  $P(\text{Holmes' lawn} | \text{Rain}, \text{Sprinkler})$ .

The hypothesis under consideration is  $\text{Sprinkler} = \text{yes}$ .

- (a) Identify the set of evidence.
- (b) What is the impact of subsets of the evidence on the hypothesis?

Rain	Gibbon's lawn	
	dry	wet
no	0.9	0.1
yes	0.1	0.99

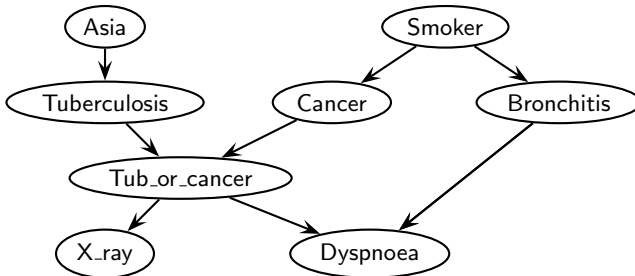
**Table 10.8.** The conditional probability distribution  $P(\text{Gibbon's lawn}|\text{Rain})$ .

Rain	Watson's lawn	
	dry	wet
no	0.9	0.1
yes	0.1	0.99

**Table 10.9.** The conditional probability distribution  $P(\text{Watson's lawn}|\text{Rain})$ .

- (c) What subsets of the evidence discriminate the hypothesis from the alternative hypothesis  $\text{Rain} = \text{yes}$ ?
- (d) How does the posterior distribution of the hypothesis change with changes in the observed state for each evidence variable?
- (e) What is the impact of each individual piece of evidence on the posterior distribution of the hypothesis?

**Exercise 10.2.** Consider the Asia network shown in Figure 10.5 (see Example 4.2 on page 68 for more details).



**Fig. 10.5.** A graph specifying the independence and dependence relations of the Asia example.

The Asia network consists of the three hypothesis variables **Bronchitis**, **Cancer**, and **Tuberculosis**. The risk factors are **Smoking** and a recent visit to **Asia** while the symptoms of the network are **X\_ray** and **Dyspnoea**. The risk factors and symptoms are the possible observations a physician can make on a patient.

Assume the physician is diagnosing a smoking patient with dyspnoea who has recently been to Asia. The hypothesis under consideration is **Bronchitis = yes**.

- (a) Identify the set of evidence.
- (b) What is the impact of subsets of the evidence on the hypothesis?
- (c) What subsets of the evidence discriminate the hypothesis from the alternative hypothesis **Cancer = yes**?
- (d) How does the posterior distribution of the hypothesis change with changes in the observed state for each evidence variable?
- (e) What is the impact of each individual piece of evidence on the posterior distribution of the hypothesis?

**Exercise 10.3.** One in a thousand people has a prevalence for a particular heart disease. There is a test to detect this disease. The test is 100% accurate for people who have the disease and is 95% accurate for those who do not (this means that 5% of people who do not have the disease will be wrongly diagnosed as having it).

- (a) If a randomly selected person tests positive, what is the probability that the person actually has the heart disease?
- (b) Compute the sensitivity function  $f(t) = P(\text{Heart\_Disease} = \text{yes} | \text{Test} = \text{yes})(t)$  where  $t = P(\text{Heart\_Disease} = \text{yes})$ .
- (c) Compute the sensitivity value for  $t_0 = 0.001$ .
- (d) Identify the admissible deviation of  $t$ .

**Exercise 10.4.** Let us consider parameter sensitivity analysis in the Wet Grass network (cf. Exercise 10.1).

- (a) Compute the sensitivity function  $f(t) = P(\text{Sprinkler} = \text{yes} | \text{Holmes' lawn} = \text{wet}, \text{Watson's lawn} = \text{dry})(t)$  where  $t = P(\text{Rain} = \text{yes})$ .
- (b) Compute the sensitivity value for  $t_0 = 0.2$ .
- (c) Compute the sensitivity function  $f(t) = P(\text{Rain} = \text{yes} | \text{Holmes' lawn} = \text{wet}, \text{Watson's lawn} = \text{dry})(t)$  where  $t = P(\text{Rain} = \text{yes})$ .
- (d) Identify the admissible deviation of  $t$  when the hypothesis is **Sprinkler = yes** and the alternative hypothesis is **Rain = yes**.

## Value of Information Analysis

Probabilistic networks are constructed to support reasoning and decision making under uncertainty. A common solution to a reasoning problem is the posterior probability distribution over a hypothesis variable given a set of evidence. Similarly, the solution to a decision making problem is an optimal decision given a set of evidence. When faced with a reasoning or decision making problem, we may have the option to consult additional information sources for further information that may improve the solution. Value of information analysis is a tool for analyzing the potential usefulness of additional information before the information source is consulted.

We consider a one-step look-ahead hypothesis driven approach to value of information (VOI) analysis. At any time, at most one additional information source may be consulted in the search for additional information. In the case of a reasoning problem we assume that the posterior probability distribution of a certain hypothesis variable is of interest and that a set of evidence is available. The task of value of information analysis is to determine the value of information from different information sources; i.e., the value of making additional observations before accepting the posterior distribution of the hypothesis as the solution to the reasoning problem. On the other hand, in the case of a decision making problem we assume that we are about to make a certain decision based on a set of observations on its relevant past. Again the task of value of information analysis is to consider the value of information from different information sources; i.e., the value of making additional observations before making a decision based on the current expected utility function over the decision options available.

In Section 11.1 we describe value of information analysis in Bayesian networks. The value of information analysis in Bayesian networks is based on an information theoretic approach using concepts such as entropy, mutual information, and information gain. Entropy and mutual information are introduced as *information measures* specifying the information gain by observing a variable. These information measures are easy to compute using probabilistic inference. In Section 11.2 we describe value of information analysis in influence

diagrams where the change in expected utility is used as the information measure. In both sections we consider a one-step look-ahead hypothesis driven approach to value of information analysis where we assume at most a single information source may be consulted in a quest for additional information.

## 11.1 VOI Analysis in Bayesian Networks

Consider the situation where a decision maker has to make a decision based on the probability distribution of a hypothesis variable. It could, for instance, be a physician deciding on a treatment of a patient given the probability distribution of a disease variable. For instance, if the probability of the patient suffering from the disease is above a certain threshold, then the patient should be treated immediately. Prior to deciding on a treatment the physician may have the option to gather additional information about the patient such as performing a test or asking a certain question. Given a range of options, what option should the physician choose next? That is, which of the given options will (on average) produce the most information? These questions can be answered by a value of information analysis.

Given a Bayesian network model and a hypothesis variable, the task is to identify the variable which is most informative with respect to the hypothesis variable. Hence, we consider a one-step look-ahead hypothesis driven value of information analysis in Bayesian networks.

### 11.1.1 Entropy and Mutual Information

The main reason for acquiring additional information is to decrease the uncertainty about the hypothesis under consideration. The selection of the variable to observe next (e.g., the question to ask next) can be based on the notion of *entropy*. Entropy is a measure of how much the probability mass is scattered over the states of a variable (the degree of chaos in the distribution of the variable), see Cover & Thomas (1991). As such entropy is a measure of randomness. The more random a variable is, the higher its entropy will be.

Let  $X$  be a discrete random variable with  $n$  states  $x_1, \dots, x_n$  and probability distribution  $P(X)$ , then the entropy of  $X$  is defined as

$$\begin{aligned} H(X) &= -\mathbb{E}_{P(X)}[\log P(X)] \\ &= -\sum_x P(X) \log P(X) \\ &\geq 0. \end{aligned}$$

The maximum entropy,  $\log(n)$ , is achieved when the probability distribution,  $P(X)$ , is uniform while the minimum entropy, 0, is achieved when all the probability mass is located on a single state. Thus,  $H(X) \in [0, \log(n)]$ .

Since entropy can be used as a measure of the uncertainty in the distribution of a variable, we can determine how the entropy of a variable changes as observations are made. In particular, we can identify the most informative observation.

If  $Y$  is a random variable, then the entropy of  $X$  given an observation on  $Y$  is

$$\begin{aligned} H(X|Y) &= -\mathbb{E}_{P(X,Y)}[\log P(X|Y)] \\ &= -\sum_Y P(Y) \sum_X P(X|Y) \log P(X|Y) \\ &= H(X) - I(X, Y), \end{aligned}$$

where  $I(X, Y)$  is the *mutual information* (also known as *cross entropy*) of  $X$  and  $Y$ . The *conditional entropy*  $H(X|Y)$  is a measure of the uncertainty of  $X$  given an observation on  $Y$ , while the mutual information  $I(X, Y)$  is a measure of the information shared by  $X$  and  $Y$  (i.e., the reduction in entropy from observing  $Y$ ). If  $X$  is the variable of interest, then  $I(X, Y)$  is a measure of the value of observing  $Y$ . The mutual information is computed as

$$\begin{aligned} I(X, Y) &= H(X) - H(X|Y) \\ &= H(Y) - H(Y|X) \\ &= \sum_Y P(Y) \sum_X P(X|Y) \log \frac{P(X, Y)}{P(X)P(Y)}. \end{aligned}$$

In principle,  $I(X, Y)$  is a measure of the distance between  $P(X)P(Y)$  and  $P(X, Y)$ . The *conditional mutual information* given a set of evidence  $\varepsilon$  is computed by conditioning the probability distributions on the available evidence  $\varepsilon$ :

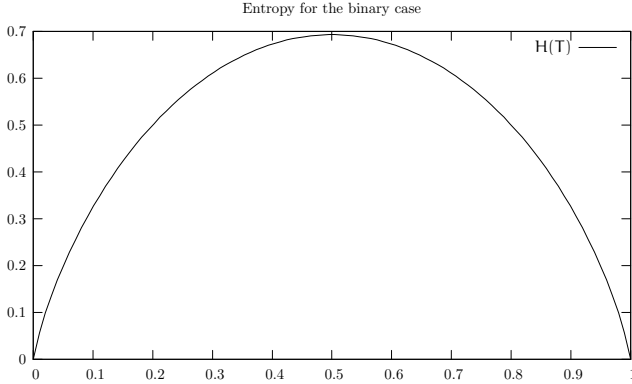
$$I(X, Y|\varepsilon) = \sum_Y P(Y|\varepsilon) \sum_X P(X|Y, \varepsilon) \log \frac{P(X, Y|\varepsilon)}{P(X|\varepsilon)P(Y|\varepsilon)}.$$

We compute  $I(X, Y|\varepsilon)$  for each possible observation  $Y$ . The next variable to observe is the variable  $Y$  that has the highest non-zero mutual information with  $X$  (i.e.,  $I(X, Y|\varepsilon)$ ), if any.

The probabilities needed for the computation of mutual information are readily computed by message passing in a junction tree representation of the model.

### 11.1.2 Hypothesis Driven Value of Information Analysis

Value of information analysis is the task of estimating the value of additional information. When considering hypothesis driven value of information analysis in Bayesian networks, we need to define a *value function* in order to determine the value of an information scenario. Entropy can be used as a value function.



**Fig. 11.1.** The entropy of  $T$ .

In a hypothesis driven value of information analysis the value of an information scenario is defined in terms of the probability distribution of the hypothesis variable. If  $T$  is the hypothesis variable and entropy is used as the value function, then the value function is defined as

$$V(T) = -H(T) = \sum_T P(T) \log(P(T)).$$

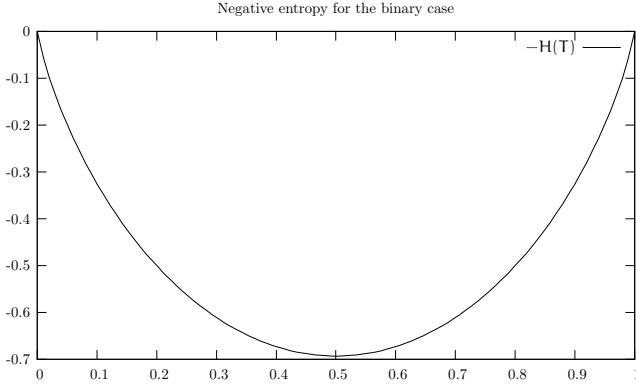
The reason for using the negation of the entropy is best illustrated using an example. Consider a binary hypothesis variable  $T$  with states **false** and **true**. Hence, the distribution of  $T$  is fully specified by a single parameter  $p$ ; i.e.,  $P(T = \text{false}, T = \text{true}) = (p, 1 - p)$ . Figure 11.1 illustrates the entropy as a function of  $p$  while Figure 11.2 illustrates the negation of the entropy as a function of  $p$ .

As can be seen from Figure 11.1 the entropy takes on its maximum value for the uniform distribution and its minimum value for the extreme cases ( $p = 0$  and  $p = 1$ ). Since the value function should take on its maximum value at the extreme cases and the minimum value in the uniform case, the negation of the entropy is used as the value function as illustrated in Figure 11.2.

The value of the information scenario after observing a variable  $X$  is

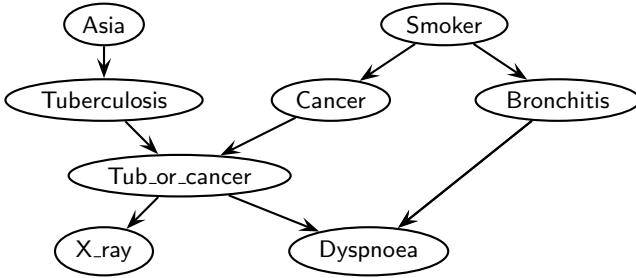
$$V(T|X) = -(H(T) - I(X, T)).$$

Thus, one-step look-ahead hypothesis driven value of information analysis in Bayesian networks amounts to computing the value of the initial information scenario  $V(T)$  and the value of information scenarios where a variable  $X$  is observed, i.e.,  $V(T|X)$ . The task is to identify the variable that increases the value of information the most. The most informative variable to observe is the variable with the highest mutual information with the hypothesis variable.



**Fig. 11.2.** The negation of the entropy of  $T$ .

*Example 11.1.* As an example we consider a one-step look-ahead hypothesis driven value of information analysis on the Asia example shown in Figure 11.3. The hypothesis variable is Bronchitis ( $B$ ) and the initial set of evidence is  $\varepsilon = \emptyset$ . That is, we are considering whether or not the patient is suffering from bronchitis.



**Fig. 11.3.** A graph specifying the independence and dependence relations of the Asia example.

Given the network of Figure 11.3, the hypothesis variable Bronchitis, and the initial set of evidence  $\varepsilon = \{\varepsilon_D\} = \{D = \text{yes}\}$ , we want to determine the most valuable observation. We may compute the value of the initial information scenario as



$$\begin{aligned} V(\text{Bronchitis}) &= -H(\text{Bronchitis}) \\ &= - \sum_{x \in \{\text{no}, \text{yes}\}} P(\text{Bronchitis} = x) \log P(\text{Bronchitis} = x) \\ &= -0.69, \end{aligned}$$

where

$$\begin{aligned} P(\text{Bronchitis} = \text{yes}) &= 1 - P(\text{Bronchitis} = \text{no}) \\ &= 0.45; \end{aligned}$$

i.e.,  $P(\text{Bronchitis}) = (\text{yes}, \text{no}) = (0.55, 0.45)$ .

To identify the most informative observation, we compute the mutual information between the hypothesis variable and each of the other variables in the model. Table 11.1 specifies the mutual information between **Bronchitis** and each of the other (unobserved) variables.

Variable name (X)	I(Bronchitis, X)
Dyspnoea	0.25
Smoker	0.05
X_ray	0.0008
Asia	0

**Table 11.1.** Mutual information between **Bronchitis** and other variables given no observations.

Notice that one of the variables has a mutual information measure of value zero. A mutual information measure of zero specifies that the two variables are independent (this can be easily verified applying d-separation).

From Table 11.1 it is clear the most informative variable is **Dyspnoea**. Thus, we choose to observe this variable. Assume we observe the patient to suffer from dyspnoea; i.e., **Dyspnoea** = **yes**. The value of the new information scenario can be computed as described above

$$\begin{aligned} V(\text{Bronchitis}|\text{Dyspnoea} = \text{yes}) &= -H(\text{Bronchitis}|\text{Dyspnoea} = \text{yes}) \\ &= -0.45, \end{aligned}$$

where  $P(\text{Bronchitis}|\text{Dyspnoea} = \text{yes}) = (\text{yes}, \text{no}) = (0.834, 0.166)$ .

Once the **Dyspnoea** variable has been observed to be in state **yes** we may be satisfied with the certainty in the hypothesis or we may search for the next observation to make.

Table 11.2 shows the mutual information between **Bronchitis** and each of the remaining unobserved variables when **Dyspnoea** is observed to be in state **yes**. The variable with the highest mutual information score is **X\_ray**.

Variable name (X)	I(Bronchitis, X)
X_ray	0.014
Smoker	0.0129
Asia	0.0002

**Table 11.2.** Mutual information between Bronchitis and other variables given Dyspnoea = yes.

If the variable with the highest mutual information score is unobservable, then we proceed to the variable with the second highest score. Notice that the mutual information scores change as observations are made. Often both the score and the order of the variables will change with observations.

Variables with a score of zero should not be observed as they will not add any information to the analysis. Notice that additional information cannot decrease the value of an information scenario.

## 11.2 VOI Analysis in Influence Diagrams

The value of information is a core element of decision analysis. We perform decision analysis using influence diagram representations of decision problems. The structure of an influence diagram  $\mathcal{N} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$  specifies a partial order on observations relative to the order of decisions

$$\mathcal{I}_0 \prec \mathcal{D}_1 \prec \mathcal{I}_1 \prec \cdots \prec \mathcal{D}_n \prec \mathcal{I}_n.$$

Value of information analysis in influence diagrams considers the impact of changing the partial order of observations relative to decisions.

Assume  $\mathcal{D}_j$  is the next decision to be made and let  $\varepsilon$  be the set of observations and decisions made up to decision  $\mathcal{D}_j$ . Initially, the basis for making decision  $\mathcal{D}_j$  is the expected utility function  $EU(\mathcal{D}_j | \varepsilon)$  over the options encoded by  $\mathcal{D}_j$ .

Let  $X_i \in \mathcal{I}_k$  where  $k \geq j$  such that  $X_j \notin \mathcal{F}(\mathcal{D}_j)$  be a discrete random variable with  $n$  states  $x_1, \dots, x_n$ ; i.e.,  $X_i$  is a variable observed after  $\mathcal{D}_j$  or never observed such that  $X_i$  is not a descendant of  $\mathcal{D}_j$ . Assume  $X_i = x$  is observed prior to making decision  $\mathcal{D}_j$ . The revised basis for making decision  $\mathcal{D}_j$  is the expected utility function  $EU(\mathcal{D}_j | \varepsilon, x)$ . Prior to observing the state of  $X_i$  the probability distribution of  $X_i$  is  $P(X_i | \varepsilon)$ . Thus, we can compute the expected utility of the optimal decision at  $\mathcal{D}_j$  after  $X_i$  is observed  $EUO(X_i, \mathcal{D}_j | \varepsilon)$  to be

$$EUO(X_i, \mathcal{D}_j | \varepsilon) = \sum_{x_i} P(X_i | \varepsilon) \max_{\mathcal{D}_j} EU(\mathcal{D}_j | \varepsilon, X_i).$$

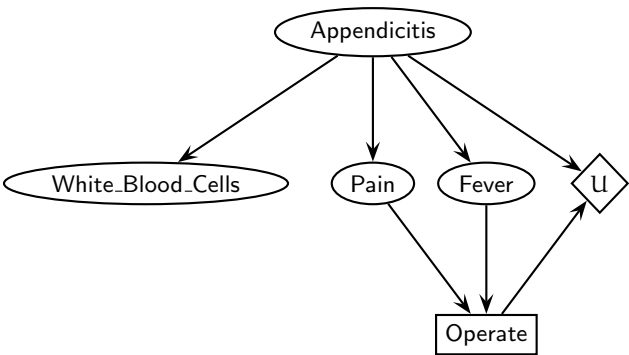
This value should be compared with the expected utility  $\max_{\mathcal{D}_j} EU(\mathcal{D}_j | \varepsilon)$  of the optimal decision at  $\mathcal{D}_j$  without the observation on  $X_i$ . The value  $VOI(X_i, \mathcal{D}_j | \varepsilon)$  of observing  $X_i$  before decision  $\mathcal{D}_j$  is

$$\text{VOI}(X_i, D_j | \epsilon) = \text{EUO}(X_i, D_j | \epsilon) - \max_{D_j} \text{EU}(D_j | \epsilon).$$

*Example 11.2 (Appendicitis).* Appendicitis may cause fever, pain, or both. If a patient has appendicitis, then the patient will have an increased count of white blood cells in addition to fever and pain. Assume that fever and pain are observed.

When a patient potentially has appendicitis, the physician may choose to operate right away or wait for the result of a blood test. The question considered is whether or not the result of the blood test provides sufficient value.

Figure 11.4 shows a graphical representation of the decision problem where we assume fever and pain are observed while the blood test result is not (yet) observed.



**Fig. 11.4.** A graph representing the Appendicitis example.

To compute the value of information on `White_Blood_Cells` the model has to be quantified. Let  $P(\text{Appendicitis} = \text{no}, \text{Appendicitis} = \text{yes}) = (0.85, 0.15)$  and the remaining conditional probability distributions be given as specified in Table 11.3–Table 11.5. Table 11.6 shows the utility function  $U(\text{Appendicitis}, \text{Operate})$ .

	Appendicitis = no	Appendicitis = yes
Fever = no	0.5	0.02
Fever = yes	0.5	0.98

**Table 11.3.** The conditional probability distribution  $P(\text{Fever}|\text{Appendicitis})$ .

	Appendicitis = no	Appendicitis = yes
Pain = no	0.4	0.05
Pain = yes	0.6	0.95

**Table 11.4.** The conditional probability distribution  $P(\text{Pain}|\text{Appendicitis})$ .

	Appendicitis = no	Appendicitis = yes
White.Blood.Cells = no	0.95	0.01
White.Blood.Cells = yes	0.05	0.99

**Table 11.5.** The conditional probability distribution  $P(\text{White.Blood.Cells}|\text{Appendicitis})$ .

Appendicitis	Operate	
no	now	5
no	wait	-5
yes	now	-10
yes	wait	10

**Table 11.6.** The utility function  $U(\text{Appendicitis}, \text{Operate})$ .

Assume that the physician observes the patient to suffer from pain and fever; i.e.,  $\varepsilon = \{\text{Fever} = \text{yes}, \text{Pain} = \text{yes}\}$ . With the above quantification we compute the expected utility function over **Operate** to be  $EU(\text{Operate}|\text{Fever} = \text{yes}, \text{Pain} = \text{yes}) = (0.31, -0.31)$ . We compute the expected utility of the optimal decision at **Operate** after **White.Blood.Cells** is observed to be

$$\begin{aligned}
 & EUO(\text{White.Blood.Cells}, \text{Operate}|\varepsilon) \\
 &= \sum_{\text{White.Blood.Cells}} P(\text{White.Blood.Cells}|\varepsilon) \\
 & \quad \max_{\text{Operate}} EU(\text{Operate}|\varepsilon, \text{White.Blood.Cells}) \\
 &= 6.375.
 \end{aligned}$$

The value of observing **White.Blood.Cells** before decision **Operate** is

$$\begin{aligned}
 & VOI(\text{White.Blood.Cells}, \text{Operate}|\varepsilon) \\
 &= EUO(\text{White.Blood.Cells}, \text{Operate}|\varepsilon) - \max_{\text{Operate}} EU(\text{Operate}|\varepsilon) \\
 &= 6.375 - 0.31 = 6.065.
 \end{aligned}$$

Thus, the physician should wait for the result of the blood test.

Instead of considering which observation to make next, if any, at a decision in the middle of the decision process, we may consider how the maximum expected utility of the optimal strategy  $\hat{\Delta}$  changes as the partial order

of observations is altered. Let  $\text{MEU}(\hat{\Delta})$  be the maximum expected utility of the original formulation of the decision problem  $\mathcal{N}$  and let  $\text{MEU}(\hat{\Delta}^*)$  be the maximum expected utility of the revised formulation of the decision problem  $\mathcal{N}^*$  where a variable  $X \in \mathcal{I}_j$  in  $\mathcal{N}$  and  $X \in \mathcal{I}_k$  in  $\mathcal{N}^*$  such that  $j > k$  and  $X \notin \mathcal{F}(\mathcal{D}_{k-1})$ . The value of observing  $X$  before decision  $k - 1$  instead of before decision  $j - 1$  is  $\text{MEU}(\hat{\Delta}^*) - \text{MEU}(\hat{\Delta})$ .

*Example 11.3.* Reconsidering the decision problem in Example 11.2, we compute the maximum expected utility  $\text{MEU}(\hat{\Delta})$  of the optimal strategy  $\hat{\Delta}$  for the information scenario where `White_Blood_Cells` is not observed before making any observation to be (where we use the first letter of each variable name to shorten the presentation)

$$\begin{aligned} \text{MEU}(\hat{\Delta}) &= \sum_P \sum_F \max_O \sum_W \sum_A P(A)P(F|A)P(P|A)P(W|A)U(O, A) \\ &= 2.99. \end{aligned}$$

Similarly, we compute the maximum expected utility  $\text{MEU}^*(\hat{\Delta}^*)$  of the optimal strategy  $\hat{\Delta}^*$  for the information scenario where `White_Blood_Cells` is observed to be

$$\begin{aligned} \text{MEU}^*(\hat{\Delta}^*) &= \sum_W \sum_P \sum_F \max_O \sum_A P(A)P(F|A)P(P|A)P(W|A)U(O, A) \\ &= 5.45. \end{aligned}$$

Based on the above analysis the physician should wait for the result of the blood test. The value of observing `White_Blood_Cells` prior to the decision is

$$\begin{aligned} \text{VOI}(\text{White\_Blood\_Cells}, \text{Operate} | \varepsilon) &= \text{MEU}^*(\hat{\Delta}^*) - \text{MEU}(\hat{\Delta}) \\ &= 5.45 - 2.99 \\ &= 2.46, \end{aligned}$$

where  $\varepsilon$  is the set of observations on `Fever` and `Pain`.

### 11.3 Summary

In this chapter we have considered value of information analysis in Bayesian networks and influence diagrams in two separate sections. In both cases we have described a one-step look-ahead approach to value of information analysis. That is, value of information analysis performed under the assumption that we may at most consult one additional information source in the search for further information before accepting the posterior distribution of the hypothesis variable or making the decision.

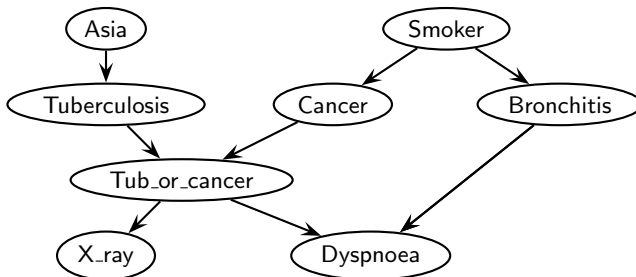
In order to perform value of information analysis in Bayesian networks we have defined entropy and mutual information as information measures.

Entropy is a measure of how much the probability mass is scattered over the states of the hypothesis variable. In the evaluation of possible information sources we identify the possible observation that reduces the entropy of the hypothesis variable the most. This will be the variable with the highest mutual information with the hypothesis variable.

In the case of value of information analysis in influence diagrams expected utility is used as the information measure. In the evaluation of possible information sources we identify the possible observation that increases the expected utility of the decision the most. This variable is identified by computing the maximum expected utility of the decision given that the variable is observed prior to the decision. This maximum expected utility is computed for each possible observation and compared with the maximum expected utility of the decision given no additional information.

## Exercises

**Exercise 11.1.** Consider the Asia network shown in Figure 11.5 (see Example 4.2 on page 68 for more details).



**Fig. 11.5.** A graph specifying the independence and dependence relations of the Asia example.

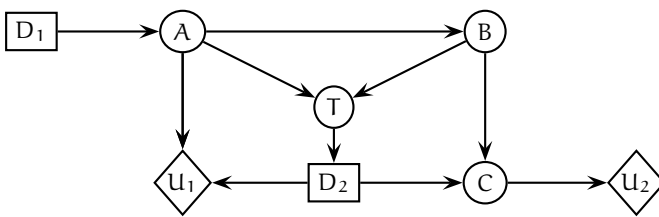
The Asia network consists of the three hypothesis variables **Bronchitis**, **Cancer**, and **Tuberculosis**. The risk factors are **Smoking** and a recent visit to **Asia** while the symptoms of the network are **X\_ray** and **Dyspnoea**. The risk factors and symptoms are the possible observations a physician can make on a patient.

- What is the entropy of the prior distribution on each of the diseases?
- What is the most informative observation with respect to each of the diseases?
- What is the most informative observation with respect to each of the diseases if the patient is a smoker suffering from dyspnoea?

**Exercise 11.2.** A used car salesman offers all potential customers a test performed on the car they are interested in buying. The test should reveal whether the car has either no defects or one (or more) defects; the prior probability that a car has one or more defects is 0.3. There are two possible tests: **Test<sub>1</sub>** has three possible outcomes, namely no-defects, defects and inconclusive. If the car does not have any defects, then the probabilities for these test results are 0.8, 0.05 and 0.15, respectively. On the other hand, if the car has defects, then the probabilities for the test results are 0.05, 0.75 and 0.2. For **Test<sub>2</sub>** there are only two possible outcomes (no-defects and defects). If the car does not have any defects, then the probabilities for the test results are 0.8 and 0.2, respectively, and if the car has defects then the probabilities are 0.25 and 0.75.

- (a) Construct a Bayesian network (both structure and probabilities) representing the relations between the two tests and the state of the car.
- (b) Calculate the probabilities  $P(\text{StateOfCar}|\text{Test}_1)$  and  $P(\text{Test}_1)$ .
- (c) Perform a value of information analysis on both **Test<sub>1</sub>** and **Test<sub>2</sub>** with respect to **StateOfCar**.

**Exercise 11.3.** Assume we are given the influence diagram in Figure 11.6.



**Fig. 11.6.** An influence diagram with two decisions.

$P(A D_1)$			$d_{11}$	$d_{12}$	$P(B A)$			$a_1$	$a_2$
$a_1$			0.3	0.6	$b_1$			0.1	0.8
$a_2$			0.7	0.4	$b_2$			0.9	0.2

$P(T A, B)$		$a_1$	$a_2$	$P(C B, D_2)$		$b_1$	$b_2$
$b_1$		(0, 1)	(0.2, 0.8)	$d_{21}$		(0.9, 0.1)	(0.5, 0.5)
$b_2$		(0.6, 0.4)	(0.8, 0.2)	$d_{22}$		(0.5, 0.5)	(0.9, 0.1)

$U_1(A, D_2)$			$a_1$	$a_2$	$U_2(C) = (20, 0)$
$d_{11}$			10	0	
$d_{12}$			0	-6	

- (a) Compute the solution to this decision problem (i.e., compute the strategy maximizing the expected utility).

- (b) Describe the impact of the information on variable  $T$ .
- (c) Repeat parts (a) and (b) when  $P(A|D_1 = d_{12}) = (0.4, 0.6)$  and  $U_2(C) = (20, 100)$ .
- (d) Assume the informational link between  $T$  and  $D_2$  is not present in the influence diagram. Compute  $VOI(T)$  when  $D_1 = d_{12}$  for both quantifications.

**Exercise 11.4.** Assume that Frank wakes up one morning feeling ill. Frank thinks that he may have caught the flu, and he now has to decide whether to go to the pharmacy to buy some medicine (at the cost of €150). If Frank has the flu, then the medicine will relieve his discomfort during the sickness period; if he does not have the flu then the medicine will have no effect. Assuming that Frank does not suffer from the discomfort caused by a flu, then he can take some additional overtime work which will be worth €2000.

Before Frank decides to go to the pharmacy, he can try to get more information by buying a thermometer (at a cost of €10.) and test whether he has a fever; the thermometer is very precise and will indicate a fever if and only if Frank actually has a fever.

- (a) Perform a myopic value of information analysis for the decision problem above and calculate the expected profit of performing the test (i.e., buying the thermometer at a cost of €10 and taking the temperature). Calculate the required probabilities from the joint probability table (over the variables Flu and Fever) specified in Table 11.7.

		Flu	
		no	yes
Fever	no	0.89298	0.00095
	yes	0.09702	0.00905

**Table 11.7.** The joint probability distribution  $P(\text{Fever}, \text{Flu})$ .



---

## References

- Andersen, S. K., Olesen, K. G., Jensen, F. V. & Jensen, F. (1989). HUGIN — a Shell for Building Bayesian Belief Universes for Expert Systems, *Proceedings of the Eleventh International Joint Conference on Artificial Intelligence*, pp. 1080–1085.
- Bender, E. A. (1996). *Mathematical Methods in Artificial Intelligence*, IEEE Computer Society Press.
- Boyer, X. & Koller, D. (1998). Tractable inference for complex stochastic processes, *Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence*, pp. 33–42.
- Castillo, E., Gutiérrez, J. M. & Hadi, A. S. (1997). Sensitivity analysis in discrete Bayesian Networks, *IEEE Transactions on Systems, Man and Cybernetics, Part A*, pp. 412–423.
- Chickering, D. M. (1996). Learning Bayesian networks is NP-complete, *Learning from Data: Artificial Intelligence and Statistics V*, pp. 121–130.
- Cobb, B. R. & Shenoy, P. P. (2004). Hybrid influence diagrams using mixtures of truncated exponentials, *Proceedings of the Twentieth Conference on Uncertainty in Artificial Intelligence*, AUA Press, Arlington, VA, pp. 85–93.
- Cooper, G. F. (1990). The computational complexity of probabilistic inference using Bayesian belief networks, *Artificial Intelligence* **42**(2–3): 393–405.
- Coupé, V. M. & van der Gaag, L. C. (1998). Practicable sensitivity analysis of Bayesian belief networks, *Prague Stochastics '98 – Proceedings of the Joint Session of the 6th Prague Symposium of Asymptotic Statistics and the 13th Prague Conference on Information Theory, Statistical Decision Functions and Random Processes*, pp. 81–86.
- Cover, T. M. & Thomas, J. A. (1991). *Elements of Information Theory*, John Wiley & Sons.
- Cowell, R. G., Dawid, A. P., Lauritzen, S. L. & Spiegelhalter, D. J. (1999). *Probabilistic Networks and Expert Systems*, Springer-Verlag.
- Dagum, P. & Luby, M. (1993). Approximating probabilistic inference in Bayesian belief networks is NP-hard, *Artificial Intelligence* **60**: 141–153.
- Dawid, A. P. (1992). Applications of a general propagation algorithm for probabilistic expert systems, *Statistics and Computing* **2**: 25–36.
- DeGroot, M. (1986). *Probability and Statistics*, second edn, Addison-Wesley. Reprint with corrections, 1989.

- Dempster, A. P. (1968). A generalization of Bayesian inference, *Journal of the Royal Statistical Society, Series B* **30**: 205–247.
- Diez, F. J. (1993). Parameter adjustment in Bayes networks, The generalized noisy OR-gate, *Proceedings of the Ninth Conference on Uncertainty in Artificial Intelligence*, pp. 99–105.
- Duda, R. O. & Hart, P. E. (1973). *Pattern Classification and Scene Analysis*, New York: John Wiley & Sons.
- Friedman, N., Geiger, D. & Goldszmidt, M. (1997). Bayesian Network classifiers, *Machine Learning*, pp. 1–37.
- Frydenberg, M. (1989). The chain graph Markov property, *Scandinavian Journal of Statistics* **17**: 333–353.
- Geiger, D., Verma, T. & Pearl, J. (1990). Identifying independence in Bayesian networks, *Networks* **20**(5): 507–534. Special Issue on Influence Diagrams.
- Heckerman, D. (1986). Probabilistic interpretations for MYCIN's certainty factors, *Uncertainty in Artificial Intelligence*, Elsevier Science Publishers B. V. (North-Holland), Amsterdam, pp. 298–312.
- Heckerman, D. (1993). Causal Independence for Knowledge Acquisition and Inference, *Proceedings of the Ninth Conference on Uncertainty in Artificial Intelligence*, pp. 122–127.
- Heckerman, D. & Breese, J. S. (1994). A New Look at Causal Independence, *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, pp. 286–292.
- Howard, R. A. & Matheson, J. E. (1981). Influence diagrams, *Readings in Decision Analysis*, Strategic Decisions Group, Menlo Park, CA, chapter 38, pp. 763–771.
- Hugin (2006). Hugin GUI Help, Hugin Expert A/S, [www.hugin.com](http://www.hugin.com). Reference Manual for the Hugin Graphical User Interface.
- Jensen, F., Jensen, F. V. & Dittmer, S. (1994). From influence diagrams to junction trees, *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, Morgan Kaufmann Publishers, San Francisco, pp. 367–373.
- Jensen, F. V. (1996). *An Introduction to Bayesian Networks*, UCL Press, London.
- Jensen, F. V. (2001). *Bayesian Networks and Decision Graphs*, Springer-Verlag.
- Jensen, F. V. & Jensen, F. (1994). Optimal Junction Trees, *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, pp. 360–366.
- Jensen, F. V., Lauritzen, S. L. & Olesen, K. G. (1990). Bayesian updating in causal probabilistic networks by local computations, *Computational Statistics Quarterly* **4**: 269–282.
- Kenley, C. R. (1986). *Influence Diagram Models with Continuous Variables*, PhD thesis, Department of Engineering-Economic Systems, Stanford University, CA.
- Kim, J. H. & Pearl, J. (1983). A computational model for causal and diagnostic reasoning in inference systems, *Proceedings of the Eighth International Joint Conference on Artificial Intelligence*, pp. 190–193.
- Kim, Y.-G. & Valtorta, M. (1995). On the Detection of Conflicts in Diagnostic Bayesian Networks Using Abstraction, *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence*, pp. 362–367.
- Kjærulff, U. B. (1995). dHugin: a computational system for dynamic time-sliced Bayesian networks, *International Journal of Forecasting* **11**: 89–111.
- Koller, D. & Pfeffer, A. (1997). Object-oriented Bayesian networks, *Proceedings of the Thirteenth Conference on Uncertainty in Artificial Intelligence*, pp. 302–313.

- Langley, P., Iba, W. & Thompson, K. (1992). An analysis of Bayesian classifiers, *Proceedings of the Eleventh National Conference on Artificial Intelligence*, pp. 223–228.
- Laskey, K. B. (1991). Conflict or surprise: Heuristics for model revision, *Proceedings of the Seventh Conference on Uncertainty in Artificial Intelligence*, pp. 197–204.
- Laskey, K. B. (1993). Sensitivity Analysis for Probability Assessments in Bayesian Networks, *Proceedings of the Ninth Conference on Uncertainty in Artificial Intelligence*, pp. 136–142.
- Laskey, K. B. & Mahoney, S. M. (1997). Network fragments: Representing knowledge for constructing probabilistic models, *Proceedings of the Thirteenth Conference on Uncertainty in Artificial Intelligence*, pp. 334–341.
- Lauritzen, S. L. (1992a). Credit Valuation Using HUGIN. Personal communication.
- Lauritzen, S. L. (1992b). Propagation of probabilities, means and variances in mixed graphical association models, *Journal of the American Statistical Association* **87**(420): 1098–1108.
- Lauritzen, S. L. (1995). The EM algorithm for graphical association models with missing data, *Computational Statistics & Analysis* **19**: 191–201.
- Lauritzen, S. L. (1996). *Graphical models*, Oxford Statistical Science Series, Clarendon Press, Oxford, England.
- Lauritzen, S. L., Dawid, A. P., Larsen, B. N. & Leimer, H.-G. (1990a). Independence properties of directed Markov fields, *Networks* **20**(5): 491–505. Special Issue on Influence Diagrams.
- Lauritzen, S. L., Dawid, A. P., Larsen, B. N. & Leimer, H. G. (1990b). Independence properties of directed Markov fields, *Networks* **20**(5): 491–505.
- Lauritzen, S. L. & Jensen, F. (2001). Stable Local Computation with Mixed Gaussian Distributions, *Statistics and Computing* **11**(2): 191–203.
- Lauritzen, S. L. & Nilsson, D. (2001). Representing and solving decision problems with limited information, *Management Science* **47**: 1238–1251.
- Lauritzen, S. L. & Spiegelhalter, D. J. (1988). Local computations with probabilities on graphical structures and their application to expert systems, *Journal of the Royal Statistical Society, Series B* **50**(2): 157–224.
- Lin, Y. & Druzdzel, M. J. (1997). Computational advantages of relevance reasoning in Bayesian networks, *Proceedings of the Thirteenth Conference on Uncertainty in Artificial Intelligence*, Morgan Kaufmann Publishers, San Francisco, pp. 342–350.
- Madsen, A. & Jensen, F. (2005). Solving linear-quadratic conditional Gaussian influence diagrams, *International Journal of Approximate Reasoning* **38**(3): 263–282.
- Madsen, A. L. (2005). A Differential Semantics of Lazy Propagation, *Proceedings of the 21st Conference on Uncertainty in Artificial Intelligence*, pp. 364–371.
- Madsen, A. L., Jensen, F., Kjærulff, U. & Lang, M. (2005). The HUGIN tool for probabilistic graphical models, *International Journal of Artificial Intelligence Tools* **14**(3): 507–543.
- Madsen, A. L. & Jensen, F. V. (1999). Lazy propagation: A junction tree inference algorithm based on lazy evaluation, *Artificial Intelligence* **113**(1–2): 203–245.
- Madsen, A. L., Nielsen, L. M. & Jensen, F. V. (1998). Probsy – a system for the calculation of probabilities in the card game bridge, *Proceedings of the Eleventh International Florida Artificial Intelligence Research Symposium Conference*, pp. 435–439.

- Madsen, A. L. & Nilsson, D. (2001). Solving Influence Diagrams using HUGIN, Shafer-Shenoy and Lazy Propagation, *Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence*, pp. 337–345.
- Meek, C. (1995). Causal inference and causal explanation with background knowledge, *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence*, pp. 403–410.
- Neil, M., Fenton, N. & Nielsen, L. M. (2000). Building Large-Scale Bayesian Networks, *The Knowledge Engineering Review* **15**(3): 257–284.
- Nielsen, T. D. (2001). Decomposition of Influence Diagrams, *Proceedings of the Sixth European Conference on Symbolic and Quantitative Approaches to Reasoning and Uncertainty*, pp. 144–155.
- Nielsen, T. D. & Jensen, F. V. (1999). Welldefined decision scenarios, *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence*, pp. 502–511.
- Olesen, K. G., Kjærulff, U., Jensen, F., Jensen, F. V., Falck, B., Andreassen, S. & Andersen, S. K. (1989). A MUNIN network for the median nerve – a case study on loops, *Applied Artificial Intelligence* **3**. Special issue: Towards Causal AI Models in Practice.
- Olmsted, S. (1983). *On representing and solving decision problems*, PhD thesis, Department of Engineering-Economic Systems, Stanford University, Stanford, CA.
- Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Series in Representation and Reasoning, Morgan Kaufmann Publishers, San Mateo, CA.
- Pearl, J. (2000). *Causality: models, reasoning, and inference*, Cambridge University Press.
- Poland, W. B. (1994). *Decision Analysis with Continuous and Discrete Variables: A Mixture Distribution Approach*, PhD thesis, Engineering-Economic Systems, Stanford University, Stanford, CA.
- Pradhan, M., Provan, G., Middleton, B. & Henrion, M. (1994). Optimal Knowledge Engineering for Large Belief Networks, *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, pp. 484–490.
- Raiffa, H. (1968). *Decision Analysis*, Addison-Wesley, Reading, MA.
- Renooij, S. (2001). Probability elicitation for belief networks: issues to consider, *The Knowledge Engineering Review* **16**(3): 255–269.
- Robinson, R. W. (1977). Counting unlabelled acyclic digraphs, *Lecture Notes in Mathematics: Combinatorial Mathematics V*, Springer-Verlag.
- Shachter, R. (1998). Bayes-Ball: The Rational Pasttime (for Determining Irrelevance and Requisite Information in Belief Networks and Influence Diagrams), *Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence*, pp. 480–487.
- Shachter, R. D. (1986). Evaluating influence diagrams, *Operations Research* **34**(6): 871–882.
- Shachter, R. D. (1990). Evidence absorption and propagation through arc reversals, *Uncertainty in Artificial Intelligence*, Elsevier Science Publishers B. V. (North-Holland), Amsterdam, pp. 173–190.
- Shachter, R. D. & Kenley, C. R. (1989). Gaussian influence diagrams, *Management Science* **35**(5): 527–549.
- Shachter, R. D. & Peot, M. A. (1992). Decision making using probabilistic inference methods, *Proceedings of the Eighth Conference on Uncertainty in Artificial Intelligence*, Morgan Kaufmann Publishers, San Mateo, CA, pp. 276–283.

- Shafer, G. (1976). *A Mathematical Theory of Evidence*, Princeton University Press.
- Shenoy, P. P. (2006). Inference in Hybrid Bayesian Networks Using Mixtures of Gaussians, *Proceedings of the 22nd Conference on Uncertainty in Artificial Intelligence*, pp. 428–436.
- Shortliffe, E. H. & Buchanan, B. G. (1975). A model of inexact reasoning in medicine, *Mathematical Biosciences* **23**: 351–379.
- Spiegelhalter, D. & Lauritzen, S. L. (1990). Sequential updating of conditional probabilities on directed graphical structures, *Networks* **20**: 579–605.
- Spirtes, P. & Glymour, C. (1991). An algorithm for fast recovery of sparse causal graphs, *Social Science Computing Review* **9**(1): 62–72.
- Spirtes, P., Glymour, C. & Scheines, R. (2000). *Causation, Prediction, and Search*, Adaptive Computation and Machine Learning, second edn, MIT Press, Cambridge, MA.
- Srinivas, S. (1993). A Generalization of the Noisy-Or Model, *Proceedings of the Ninth Conference on Uncertainty in Artificial Intelligence*, Morgan Kaufmann Publishers, pp. 208–218.
- Steck, H. & Tresp, V. (1999). Bayesian belief networks for data mining, *Proceedings of the Second Workshop "Data Mining und Data Warehousing als Grundlage moderner entscheidungsunterstuetzender Systeme"*.
- Suermondt, H. J. (1992). *Explanation in Bayesian Belief Networks*, PhD thesis, Department of Computer Science and Medicine, Stanford University, Stanford, CA.
- Titterton, D. M., Smith, A. F. M. & Makov, U. E. (1995). *Statistical Analysis of Finite Mixture Distributions*, John Wiley & Sons, New York.
- Tversky, A. & Kahneman, D. (1981). The framing of decisions and the psychology of choice, *Science* **211**.
- Verma, T. & Pearl, J. (1992). An Algorithm for Deciding if a Set of Observed Independencies Has a Causal Explanation, *Proceedings of the Eighth Conference on Uncertainty in Artificial Intelligence*, pp. 323–330.
- Vomlelová, M. & Jensen, F. (2002). An Extension of Lazy Evaluation for Influence Diagrams Avoiding Redundant Variables in the Potentials, *First European Workshop on Probabilistic Graphical Models*, pp. 186–193.
- Wang, H., Rish, I. & Ma, S. (2002). Using sensitivity analysis for selective parameter update in Bayesian network learning, *AAAI Symposium Series*.
- Wermuth, N. & Lauritzen, S. L. (1983). Graphical and recursive models for contingency tables, *Biometrika* **70**: 537–552.
- Wermuth, N. & Lauritzen, S. L. (1990). On substantive research hypotheses, conditional independence graphs and graphical chain models, *Journal of the Royal Statistical Society, Series B* **52**(1): 21–50.
- Zadeh, L. A. (1965). Fuzzy sets, *Information and Control* **8**: 338–353.
- Zadeh, L. A. & Kacprzyk, J. (eds) (1992). *Fuzzy Logic for the Management of Uncertainty*, John Wiley and Sons, New York.
- Zhang, N. L. (2004). Hierarchical latent class models for cluster analysis, *Journal of Machine Learning Research* **5**: 697–723.

---

## List of Symbols

$\triangleq$	Defined as
$\equiv$	Equivalent to
$:=$	Assignment
$\propto$	Proportional to
$\ \cdot\ $	Domain size (i.e., $\ X\  =  \text{dom}(X) $ )
$\perp$	Independent
$\perp_p$	Independent with respect to distribution $p$
$\not\perp$	Dependent
$\not\perp_p$	Dependent with respect to distribution $p$
$\perp_d$	d-separated
$\perp_{\mathcal{G}}$	d-separated in graph $\mathcal{G}$
$\not\perp_d$	d-connected
$\not\perp_{\mathcal{G}}$	d-connected in graph $\mathcal{G}$
$\mathcal{S}$	Separator set
$\mathcal{E}$	Evidence function (potential)
$\varepsilon$	Evidence
$\mathcal{E}_{\varepsilon}$	Evidence function for $\mathcal{X}(\varepsilon)$
$\eta$	Normalization operator
$\sim$	Connected
$\rightarrow$	Connected by directed edge
$\leftarrow$	Connected by directed edge
$-$	Connected by undirected edge
$\overset{\mathcal{G}}{\sim}$	Connected in graph $\mathcal{G}$
$\overset{\mathcal{G}}{\rightarrow}$	Connected by directed edge in graph $\mathcal{G}$
$\overset{\mathcal{G}}{-}$	Connected by undirected edge in graph $\mathcal{G}$
$\not\sim$	Not connected
$\overset{\mathcal{G}}{\not\sim}$	Not connected in graph $\mathcal{G}$
$\langle u, \dots, v \rangle$	Path from $u$ to $v$
$\text{dom}$	Domain (of variable or set of variables)

	“given” (e.g., “ $\mathbf{a} \mathbf{b}$ ” means “ $\mathbf{a}$ given $\mathbf{b}$ ”)
pa	Parents of
fa	Family of
ch	Children of
an	Ancestors of
An	Ancestral set of
de	Descendants of
nd	Non-descendants of
true	Boolean value “true”
false	Boolean value “false”
$\mathcal{I}$	Past
EU	Expected utility
MEU	Maximum expected utility
$\mathbb{N}$	Normal (Gaussian) distribution
$\mathbb{N}_k$	k-dimensional Normal distribution
$\mathcal{L}$	Law of (e.g., $\mathcal{L}(\mathbf{X}) = \mathbb{N}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$ , also denoted $\mathbf{X} \sim \mathbb{N}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$ )
$\mathbb{R}$	The set of all real numbers
$\mathcal{S}$	Scope
$\mathcal{I}$	Input variables
$\mathcal{H}$	Private (hidden) variables
$\mathcal{O}$	Output variables
$\mathcal{P}$	Public variables (input + output)
$\mathcal{X}(\varepsilon)$	Evidence variables (i.e., subset of $\mathcal{X}$ for which their values are known)

---

# Index

- EUO, 297  
 $\sum$ -max- $\sum$ -rule, *see* influence diagram
- $\sim$ , 19  
 $\|\cdot\|$ , 21  
 $\rightarrow$ , *see* edge, directed  
 $\xrightarrow{g}$ , *see* edge, directed  
 $\overset{g}{\rightarrow}$ , *see* edge, undirected  
 $\text{---}$ , *see* edge, undirected  
abductive reasoning, *see* reasoning,  
    abductive  
acyclic directed graph, *see* graph,  
    acyclic directed  
AIC, *see* Akaike's Information Criterion  
Akaike's Information Criterion, 249  
almost equal, 280  
ambiguous region, 242  
An, *see* ancestral set  
an, *see* ancestor  
ancestor, 19  
ancestral set, 20  
Appendicitis, 298, 300  
Apple Jack, 66, 80  
arc, *see* edge  
arc reversal, 52, 111  
Asia, 68, 261, 267, 274, 295  
auxiliary variable, 199, 218  
axioms, *see* probability axioms
- barren variable, *see* variable, barren  
Bayes' factor, 53, 278  
Bayes' rule, 50  
    interpretation of, 51  
Bayesian Information Criterion, 249  
Bayesian likelihood ratio, 278  
Bayesian network  
    conditional LG, 72, 70–75  
    direct inference approach, 111  
    discrete, 65, 65–70  
    indirect inference approach, 121  
    query, 110  
    query based inference, 110  
belief theory, 4  
BIC, *see* Bayesian Information Criterion  
Burglary or Earthquake, 25
- case  
    complete, 246  
category, *see* variable, category  
causal network, 25–31  
    converging connection in, 29–30  
    diverging connection in, 28–29  
    flow of information in, 25–31  
    serial connection in, 26–27  
    types of connections in, 26  
causal reasoning, *see* reasoning, causal  
causality, 6, 24–25, 66  
    modeling, 30  
causally independent, 205  
cause variables, 178, 182, 205  
causes, 205  
certainty factor, 7  
ch, *see* child  
chain graph, *see* graph, chain  
chain rule, 8, 58



- Bayesian networks, 59, 65
- CLG Bayesian networks, 72
- CLQG influence diagrams, 86
- influence diagrams, 76
- object-oriented Bayesian network models, 96
- Chest Clinic, *see* Asia
- junction tree, 117
- child, 19
- chord, 117
- CLG Bayesian network, *see* Bayesian network, conditional LG
- CLG distribution, *see* conditional linear Gaussian distribution
- clique, 114
- CLQG influence diagram, *see* influence diagram, conditional LQG, 86
- collider, 231
- combination, *see* probability potential, combination
- conditional independence, *see* independence
- conditional linear Gaussian distribution, 71
- conditional linear-quadratic Gaussian influence diagram, *see* influence diagram, conditional LQG
- conditional probability, *see* probability, conditional
- conflict analysis, 261
  - local conflict, 265
  - partial conflict, 265
  - rare case, 265
- conflict measure, 262
- constraint variable, 149, 189
- contribution variable, 206
- converging connection, *see* causal network, converging connection in
- cost of omission, 267, 275
  - threshold, 268
- cycle, 20
  - directed, 20
  - full control, 223
- decision future, 79
- decision history, 78
- decision past, 79
- decision problem
  - well-defined, 80
- decision variable, 74
  - informational parents, 84
- decision variables
  - partial order, 78
  - total order, 80
- deductive reasoning, *see* reasoning, deductive
- default inhibitor, 206, 207
- default prior probability distribution, 94
- degrees of freedom, 232
- descendant, 19
- dHugin, 101
- diagnostic reasoning, *see* reasoning, diagnostic
- directed acyclic graph, *see* graph, acyclic directed
- directed cycle, *see* cycle, directed
- directed global Markov criterion, 32, 34
- directed global Markov property, 59
- directed graph, *see* graph, directed
- dissemination of experience, 252
- distance measure, 274
- distinguished state, 209
- distributive law, *see* probability calculus, distributive law of
- diverging connection, *see* causal network, diverging connection in
- division, *see* probability potential, division
  - by zero, 46, 50
- dom, *see* variable, domain
- dynamic Bayesian network, 100
- edge, 18
  - derived direction, 237
  - directed, 18
  - undirected, 19
- effect variable, 178, 182, 205
- elicitation of numbers, *see* parameters, elicitation of
- D-map, 56
- d-separation, 32, 59
- DAG, *see* graph, acyclic directed
- DAG faithfulness assumption, 230
- de, *see* descendant
- decision

- elicitation of structure, *see* structure, elicitation of
- elimination order, 115
  - strong, 123, 125
- EM algorithm
  - penalized, 249
- entropy, 292
  - conditional, 293
  - conditional mutual information, 293
  - cross, 293
  - mutual information, 293
- equivalence class, 230
- equivalent sample size, 252
- equivalent variables, *see* variable, equivalence
- event, 38
- evidence, 23
  - cost of omission, 267
  - hard, 23
  - impact, 267
  - likelihood, *see* evidence, soft
  - potential, 45
  - soft, 23
  - sufficient, 280
- expected utility, 75
- experience count, 250, 252
- experience table, 250
- expert system, 3, 107
  - normative, 5
- explaining away, 7, 18, 30
- expressions, *see* parameter, elicitation of
- factorization
  - recursive, *see* probability distribution, recursive factorization of
- faithfulness assumption, 228
- filtering, 99
- finding
  - important, 280
  - irrelevant, 280
  - redundant, 280
- flat network, 96
- functional uncertainty, 186
- fundamental rule, 39, 50
- fuzzy logic, 5
- gamble-based approach, *see* parameter, elicitation of
- generalized marginalization operator, 127
- global conflict, 265
- graph
  - acyclic directed, 20
  - chain, 17
  - condition, 243
  - connected, 20
  - directed, 19
  - equivalence class, 231
  - instances, 92
  - moral, 20
  - moralization, 114
  - skeleton, 20, 231, 236
  - strongly connected component, 243
  - undirected, 19
- head, 114
- head-to-head, 19
- Hugin algorithm, 119
- hypothesis variables, 68
- I-map, 56
- IC algorithm, 235
- idioms, 154
- independence, 54
  - completeness of DAG, 56
  - conditional, 55
  - correctness of DAG, 56
  - represented in DAGs, 56
- independence of causal influence, 205
- inference engine, 107
- influence diagram, 74
  - $\sum$ -max- $\sum$ -rule, 124
  - conditional LQG, 86, 85–89
  - discrete, 75, 75–85
  - information sets, 78
  - limited memory, 89, 89–91
    - minimal reduction, 135
    - soluble, 136
- linear-quadratic CG
  - $\sum$ -max- $\sum$ -rule, 129
- maximum expected utility, 78
- no-forgetting links, 84
- policy, 79
- policy function, 125
- strategy, 78

- optimal, 78
- information measures, 291
- informational link, *see* link, informational, 216, 218
- inheritance, 98
- inhibitor probability, 206
- initial assessment, 283
- instance, 92
- inter-causal reasoning, *see* explaining away
- interface, 99
- interface variables, 92
- intermediate variables, 178
- intervening action, 75
- intervening decision, 80
- intervention, 202
- joint probability distribution, *see* probability distribution
- junction tree, 116
  - COLLECTINFORMATION, 118
  - DISTRIBUTEINFORMATION, 118
  - propagation, 117
  - root, 118
- kind, *see* variable, kind
- law of parsimony, 171
- leak probability, 206
- likelihood evidence, *see* evidence, soft
- LIMID, *see* influence diagram, limited memory
- link, *see* edge
  - informational, 76
- local conflict, 265
- marginalization, 42, 46
  - generalized operator, 127
- Markov criterion, *see* directed global Markov criterion
- Markovian, 99
- maximum expected utility principle, 75
- measurement uncertainty, 196
- mediating variable, 178, 179, 181, 191
- MEU
  - maximum expected utility, 125
- minimal conditioning set, 241
- minimal reduction, *see* influence diagram, limited memory, minimal reduction
- missing data mechanism, 229
- Mixture of Gaussian distributions, 210
- model verification, 159
- modeling technique
  - parent divorcing, 178
- monotonicity, 264
- moral graph, *see* graph, moral
- multivariate Gaussian distribution, 71
- mutually exclusive states, 65, 71
- nd, *see* non-descendants
- necessary path condition, 241
- network class, 92
  - default instance, 97
  - internal scope, 93
- neural network, 15
- no-forgetting, 76
- node absorption, 201
- Noisy-MAX, 209
- Noisy-OR, 205
- non-descendants, 20
- non-intervening action, 75
- normalization, *see* probability potential, normalization of
- normalization constant, 109
- normalized likelihood, 51, 265, 277
- nuisance variable, *see* variable, nuisance, 201
- object, 92
- object-oriented probabilistic network, 91–98
  - instance tree, 97
  - object-orientation
    - classes, 92
    - definition, 91
    - inheritance, 92
    - objects, 92
- observation
  - essential, 131
  - requisite, 131
- Occam's Razor, 171
- Oil Wildcatter, 88
- OoBN, *see* object-oriented probabilistic network

- pa, *see* parent
- parameters
  - elicitation of, 163
- parent, 19
- partial conflict, 265
- partial order, 216
- path, 19
  - blocked in DAG, 32
  - blocked in undirected graph, 20
  - directed, 19
- PC algorithm, 235
- PDAG, 231
- perfect map, 56
- perfect recall, *see* no-forgetting
- poly-tree, 110
- posterior probability distribution, *see*
  - probability distribution, posterior
- potential calculus, 46
- prediction, 99
- probabilistic network
  - characteristics, 145
  - when to use, 144
- probability
  - conditional, 38
- probability axioms, 39
- probability calculus, 46
  - chain rule of, 58
  - distributive law of, 47
  - fundamental rule of, 39, 50
- probability distribution
  - decomposition, 37
  - for variables, 40
  - graphical representation of conditional, 43
  - marginal, 43
  - posterior, 45
  - recursive factorization of, 37
- probability of future decisions, 135
- probability potential, 44
  - combination, 46
  - division, 46
  - marginalization, *see* marginalization
  - normalization of, 44, 45
  - vacuous, 44
- process
  - underlying distribution, 228
- projection, *see* marginalization
- propagation, *see* junction tree,
  - propagation
- reasoning
  - abductive, 18
  - causal, 18
  - deductive, 18
  - diagnostic, 18
  - inter-causal, *see* explaining away
- recursive factorization, *see* probability distribution, recursive
  - factorization of
- relevant network, 111
- relevant variable, 131
- retrieval of experience, 252
- rule of total probability, 41
- rule-based system, 5
- selector variable, 184
- sensitivity function, 282
- sensitivity value, 285
- serial connection, *see* causal network,
  - serial connection in
- Single Policy Updating, 133
- skeleton, *see* graph, skeleton
- smoothing, 99
- soluble, *see* influence diagram, limited
  - memory, soluble
- Sore Throat, 207
- SPU, *see* Single Policy Updating
- stability assumption, 228
- straw model, 262
- structure
  - elicitation of, 152
  - uncertainty, 184
  - verification, *see* model verification
- subclass, 98
- subtype, *see* variable, subtype
- tail, 114
- temporal links, 99
- temporal order, 182
- test decision, 212
- time-sliced Bayesian network, 100
- topological ordering, 58
- tree, 20
- Type I error, 235
- Type II error, 235
- undirected dependence relation, 189
- undirected graph, *see* graph, undirected
- unfolded network, 96

- utility function, 74
- v-structure, *see* collider
- vacuous potential, *see* probability
  - potential, vacuous
- value function, *see* utility function, 293
- value nodes, 75
- variable, 20–23
  - barren, 49, 83, 110
  - basic, 92
  - binding link, 94
  - bound, 94
  - category, 22
  - chance, 21
  - conditioned, 65
  - conditioning, 65
  - decision, 21
  - decision future, 79
  - decision history, 78
  - decision past, 79
  - designated state, 205
  - deterministic, 21
  - domain, 21
  - elimination, 111, 115
  - equivalence, 94
  - extremal decision, 136
  - hidden, latent, 229
  - identification of, 147
  - independence, *see* dependence and independence
  - kind, 22
  - no impact state, 205
  - nuisance, 111
  - policy, 79
  - qualified name, 93
  - random, 21
  - scope, 93
  - set by intervention, 203
  - simple name, 93
  - strong marginal, 122
  - strong type checking, 94
  - subtype, 22, 166
  - synergy, 209
  - target, 110
  - taxonomy, 22
  - type, 150
  - vs. vertex, 21
  - weak marginal, 122
  - well-defined, 147
- vertex
  - symbols, 23
  - vs. variable, 21