3

Bayesian Programming and Modelling

So far as the theories of mathematics are about reality, they are not certain; so far as they are certain, they are not about reality.
Sidelights on Relativity (Geometry and Experience), *Albert Einstein (1923)*

Mathematics is the art of giving the same name to different things.
Science and method, *Henri Poincaré (1914)*

A problem well stated is a problem half solved.
Charles Kettering (1876-1958)

3.1 Introduction

A vast amount of different formalisms exist for the construction of probabilistic models (Fig. 3.1):

- General formalisms, which allow the construction of more encompassing and potentially more complete models.
- Specific formalisms, which yield simpler or more intuitive formulations, thus allowing for easier or more efficient computation.

An essential step to adopting probabilistic approaches to robotic perception is to become aware of the range of available modelling formalisms and also of the most important inference techniques that support model implementation.

We have briefly introduced Bayesian networks in Chapter 1; we will cover this subject in more detail on the following section, and present several supporting examples. Next, we will present the notion of probabilistic loops, for which we will introduce the concepts behind the respective formalisms. Subsequently, we will present the ultimate generalisation for Bayesian modelling – the Bayesian programming formalism – and discuss its advantages comparing to graphical models. Finally, we will offer an overview of Bayesian inference techniques and very brief list of useful implementation tools available to the modeller.

J.F. Ferreira and J. Dias: *Probabilistic Approaches for Robotic Perception*, Springer Tracts in Advanced Robotics 91,
DOI: 10.1007/978-3-319-02006-8_3,

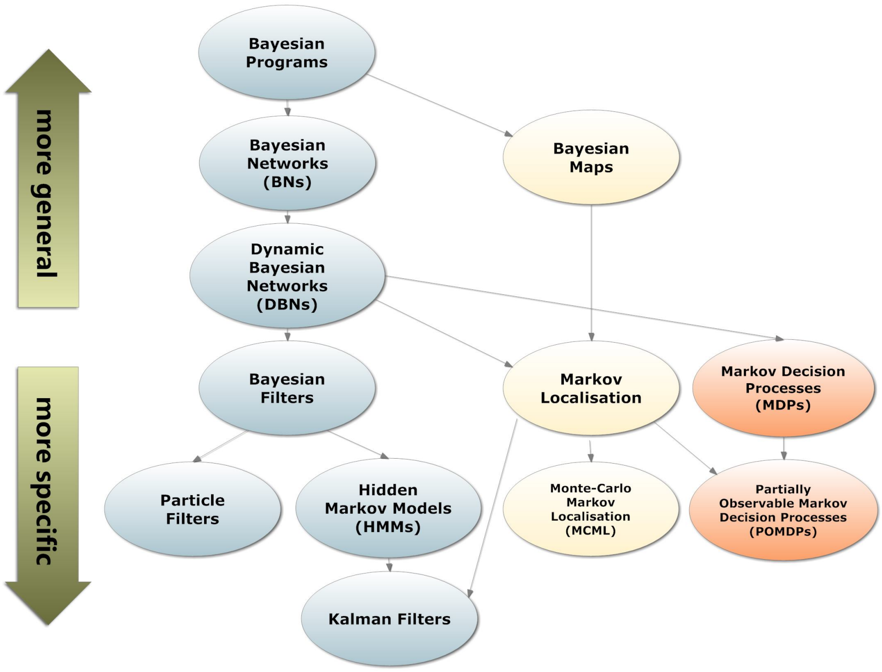

Fig. 3.1. Taxonomy of Bayesian formalisms for probabilistic model construction (adapted from [7]). As shown in the diagram, these formalisms range from general to specific, and the arrows show how specific formalisms are derived from and related to general formalisms. For example, a dynamic Bayesian network is capable of formalising the same model as a Bayesian filter (the arrow flows from the former to the latter), but not all Bayesian networks can be represented as dynamic Bayesian networks (the arrow flows from the latter to the former). Formalisms on the far left and centre left lanes have generic applications: they will be introduced in this chapter. Formalisms in the centre right lane are used for mapping and localisation applications, while formalisms in far right lane are used for decision processes, and both will be presented in Chapter 5.

3.2 Bayesian Formalisms for Probabilistic Model Construction

3.2.1 Bayesian Networks Revisited and the Plate Notation

Also called belief networks, Bayesian networks (BNs), as we have already seen in Chapter 1, are graphical models that represent a set of random variables and their conditional dependencies via directed acyclic graphs (DAG – directed graphs with no loops formed by directed cycles). Bayesian networks generally represent causal relationships through the directed edges, but there have been exceptions where they represent dependences, i.e., the inverse direction.