4

Hierarchical Combination of Bayesian Models and Representations

...any large computation should be split up into a collection of small, nearly independent, specialized subprocesses.

Vision*, David Marr (1982)*

The hierarchy of relations from the molecular structure of carbon to the equilibrium of the species and the ecological whole, will perhaps be the leading idea of the future.

Order and Life*, Joseph Needham (1923)*

4.1 Introduction

Ever since seminal work by Marr [11] and Fodor [10] up until more recent accounts such as given by Ballard [8] and many others on computational theories of perception and cognition, the link between the functional organization of perceptual sites in the brain and the underlying computational processes has led to the belief that *modularity* plays a major role in making these processes tractable. Modularity, in this sense, means that the flow of computation can be broken down into simpler processes. As a matter of fact, although the interconnections between these sites have increasingly been found to be much more intricate than Marr believed (including feedback and lateral links), the notion that the brain is organised in a modular fashion has been supported by countless findings in Neuroscience research, and is currently undisputed.

Hierarchical Bayesian methods are standard and powerful tools for analysing models and drawing inferences, and have been extensively applied in statistics, machine learning and throughout the empirical sciences [4; 1]. Hierarchical Bayesian methods provide the adequate framework for implementing modularity in perception. Firstly, these methods allow model development to take place at multiple levels of abstraction. Secondly, they offer the possibility of understanding emergent behaviour as resulting from a mixture of qualitatively and quantitatively different sources. And, thirdly, this framework is able to unify disparate models.

4.2 A Simple Hierarchical Bayesian Model

Theorists have had some difficulty in coming to terms with establishing the border between non-hierarchical and hierarchical models. To tackle this

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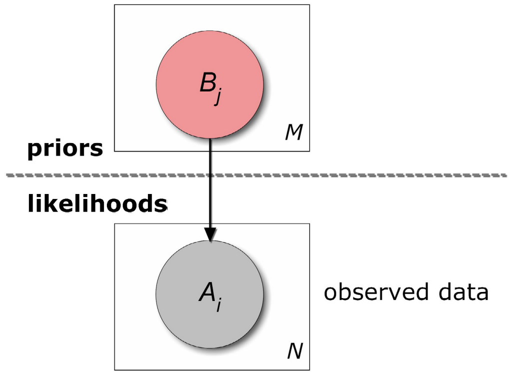

Fig. 4.1. Bayesian network for a non-hierarchical Bayesian model

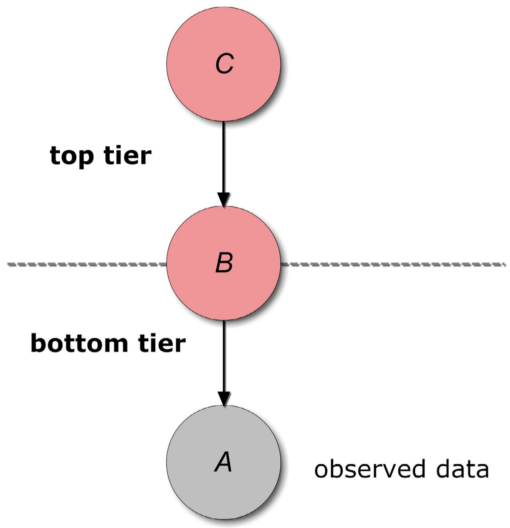

Fig. 4.2. Bayesian network for a simple two-tiered hierarchical Bayesian model. This hierarchy, which is also often called a *layered hierarchical model*, since each tier may be construed as a computational layer, can be generalised so as to involve an arbitrary number of tiers.

problem, we will attempt to simply and clearly offer our perspective on the definition of this border in formal terms.

Using an approach similar to Lee [1], we thereby define a *hierarchical Bayes model* as any generative model more complicated than the simplest type of model represented in Fig. 4.1. In the non-hierarchical model, sets of propositions represented by random variables A_i generate sets of observed data represented by random variables B_j; each of the generative variables A_i and