Hierarchical Architectures for Reasoning

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1 INTRODUCTION

This chapter has a threefold purpose: (1) to introduce a general framework for parallel/distributed computation, the computational network; (2) to expose in detail a symbolic example of a computational network, related to expert systems, called an expert network; and (3) to describe and investigate how an expert network can be realized as a neural network possessing a hierarchical symbolic/sub-symbolic architectural organization.

A computational network is essentially a directed graph in which each component (vertex or directed edge) has data processing functionality, further endowed with a concept of global network computation. Examples of computational entities that admit descriptions within the computational network model include biological neural networks, artificial neural networks, the parallel virtual machine model of loosely coupled MIMD computation, human collaborations such as committees, and expert networks. Many of the principles of neural network learning can be lifted to the level of computational networks. We present a re-examination of backpropagation learning in this context and derive the computational network backpropagation, or CNBP, learning algorithm.

An expert network is a computational network that can be obtained from an expert system. The architecture of the expert network is derived from the expert system: the network topology from the rule base, the local processing functionality of the vertices and edges from the system of inference, and the global computation concepts from the inference engine. The process of constructing an expert network from an expert system is reversible.
Expert network backpropagation, or ENBP, is a learning method for expert networks obtained as an instantiation of CNBP. ENBP has proven to be useful in knowledge refinement, allowing an expert system builder to make the transition from coarse knowledge, in the form of rough-draft rules, to fine knowledge, in the form of rules with subtlety represented by analog parameters such as certainty factors, using supervised learning and the historical record of expert behavior as a training set.

The symbolic-level nodes of an expert network can be represented by neural networks, which we view as computational networks of sub-symbolic processors. We investigate the optimal architectures for these representations, which provide a realization of an expert network as a neural network with a hierarchical topological organization: a sparsely interconnected collection of densely intraconnected neural nets. This hierarchical sparse/dense organization is analogous to biological neural organization. It captures two levels of knowledge: domain knowledge in the sparse superstructure and metaknowledge in the dense substructures. The hierarchical structural parameters are well within the connectivity constraints found in biology, making feasible the scaling up of neural-based expert networks to sizes comparable to those of living systems.

2 Computational Networks: A General Setting for Distributed Computations

A computational network is a general framework for parallel/distributed computation modeled on a directed graph in which the vertices and directed edges have computational functionality and for which there is some holistic notion of cooperative computation [32, 34]. Computational paradigms that fit within the computational network framework include biological neural networks; artificial neural networks; distributed computation on a loosely coupled collection of von-neuman machines connected to a digital communications network, as exemplified by Parallel Virtual Machine [54, 55]; human collaborative decision-making and problem-solving; and expert networks [31]. We return briefly to each of these examples after introducing computational network concepts.