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Topology of a Neural Network

Risto Miikkulainen*
Department of Computer Sciences, The University of Texas at Austin, Austin, TX, USA

Synonyms

Architecture; Connectivity; Structure; Topology

Definition

Topology of a neural network refers to the way the neurons are connected, and it is an important factor in how the network functions and learns. A common topology in unsupervised learning is a direct mapping of inputs to a collection of units that represents categories (e.g., ▸ Self-Organizing Maps). The most common topology in supervised learning is the fully connected, three-layer, feedforward network (see ▸ Backpropagation and ▸ Radial Basis Function Networks): All input values to the network are connected to all neurons in the hidden layer (hidden because they are not visible in the input or output), the outputs of the hidden neurons are connected to all neurons in the output layer, and the activations of the output neurons constitute the output of the whole network. Such networks are popular partly because they are known theoretically to be universal function approximators (with, e.g., a sigmoid or Gaussian nonlinearity in the hidden layer neurons), although networks with more layers may be easier to train in practice (e.g., ▸ Cascade-Correlation). In particular, deep learning architectures (see ▸ Deep Learning) utilize multiple hidden layers to form a hierarchy of gradually more structured representations that support a supervised task on top. Layered networks can be extended to processing sequential input and/or output by saving a copy of the hidden layer activations and using it as additional input to the hidden layer in the next time step (see ▸ Simple Recurrent Network). Fully recurrent topologies, where each neuron is connected to all other neurons (and possibly to itself), can also be used to model time-varying behavior, although such networks may be unstable and difficult to train (e.g., with backpropagation; but see also ▸ Boltzmann Machines). Modular topologies, where different parts of the networks perform distinctly different tasks, can improve stability and can also be used to model high-level behavior (e.g., ▸ Echo-State Machines and ▸ Adaptive Resonance Theory). Whatever the topology, in most cases, learning involves modifying the ▸ Weight on the network connections. However, arbitrary network topologies are possible as well and can be constructed as part of the learning (e.g., with backpropagation or ▸ Neuroevolution) to enhance feature selection, recurrent memory, abstraction, or generalization.

*E-mail: risto@cs.utexas.edu