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BIOLOGICAL AND ARTIFICIAL APPROACHES IN NEURAL NETWORKS

1.Learning in Biological Networks

In biological neural networks like the human brain, learning is achieved by making small tweaks to an existing representation – its configuration contains significant information before any learning is conducted. The strengths of connections between neurons, or weights, do not start as random, nor does the structure of the connections, i.e., the network topology. This initial state is, in part, genetically derived, and is the byproduct of evolution.

Over time, the network learns how to perform new functions by adjusting both topology and weights. The fact that there is an initial representation that works well for many tasks is supported by research, which suggests that as young as one month old newborns are able to recognize faces demonstrated by their learning to differentiate between strangers and their parents.n other words, the concept of a human face has largely been passed down genetically from parent to child.

As babies develop and progress through childhood, adolescence, adulthood, and even retirement years, they will see and meet new people every day and must learn what they look like. This is achieved by making minor alterations to the neural networks residing in their brains.

The same phenomenon applies to other tasks as well – both passive sensory tasks, from recognizing generic objects to processing sound as speech patterns, to active tasks like movement and speech. These skills are learned gradually, and progressively smaller tweaks are used to refine them. The precise topologies are a function of the types of stimuli upon which these biological neural networks are trained. A prominent example is the monocular deprivation studies led by David Hubel and Torsten Wiesel. The study involved forcing an animal's eye shut for two months during development and observing the changes to their primary visual cortex.

The results showed that cells that are normally responsive to input from both eyes, were no longer receptive at all. Both the cells in their brain and in their eye had changed as a result. This phenomenon extends to humans. For example, psychometric tests on visual perception indicates that people who have spent much of their lifetimes in cities tend to be more sensitive to parallel lines and sharp gradients than people from rural environments, who are more sensitive to smooth texture gradients, likely the result of an over-abundance of parallel structures of roads, skyscrapers, and windows.

2.Learning in Artificial Neural Networks

Unlike Biological Neural Networks, Artificial Neural Networks (ANNs), are commonly trained from scratch, using a fixed topology chosen for the problem at hand. At present, their topologies do not change over time and weights are randomly initialized and adjusted via an optimization algorithm to map aggregations of input stimuli to a desired output function. However, ANNs can also learn based on a pre-existing representation. This process is called fine-tuning and consists of adjusting the weights from a pre-trained network topology at a relatively slow learning rate to perform well on newly supplied input training data.

We can also effortlessly replicate ANNs, but we have a while to go before we can do that for a human brain.

Whether training from scratch or fine-tuning, the weight update process begins by passing data through the neural network, measuring the outcome, and modifying the weights accordingly. This overall process is how an artificial neural network "learns". Weights are gradually pushed in the directions that most increase performance of the desired task, e.g., maximizing recognition accuracy, on the input samples. This notion of learning can be likened to a child trying to learn how to recognize everyday objects. After failed attempts and feedback on the accuracy of the answer, the child tries again in a different direction to achieve the correct response. An ANN performs the same task when learning. It is fed stimuli that have known responses and a learning regime adjusts weights so as to maximize the number of accurate responses that result from feeding the ANN new stimuli.

Once this learning process is complete, both the child and the ANN can use their previous representations of the problems to craft responses to new stimuli that they have not previously been exposed to in the learning process. The child learns best via exposure to as many similar problems as possible. The more problems the child practices, the quicker he or she becomes at tackling new problems, because relevant neuronal connections in the child's brain become more defined. An ANN is similar in that with more exposure to the wide distribution of possible stimuli for the task in question, the better the ANN can learn to respond to new stimuli from the same distribution that it was not previously exposed to.

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