Non-Synaptic Learning through Modulation of Neuronal Responses

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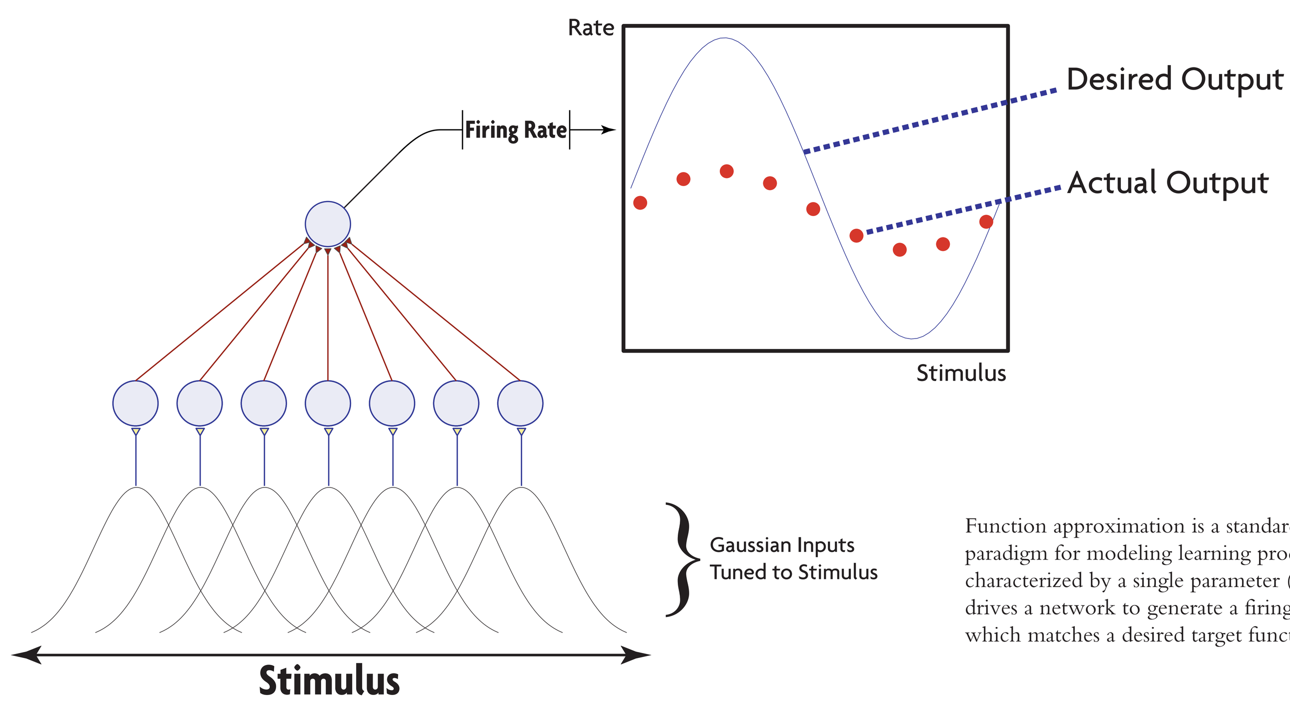
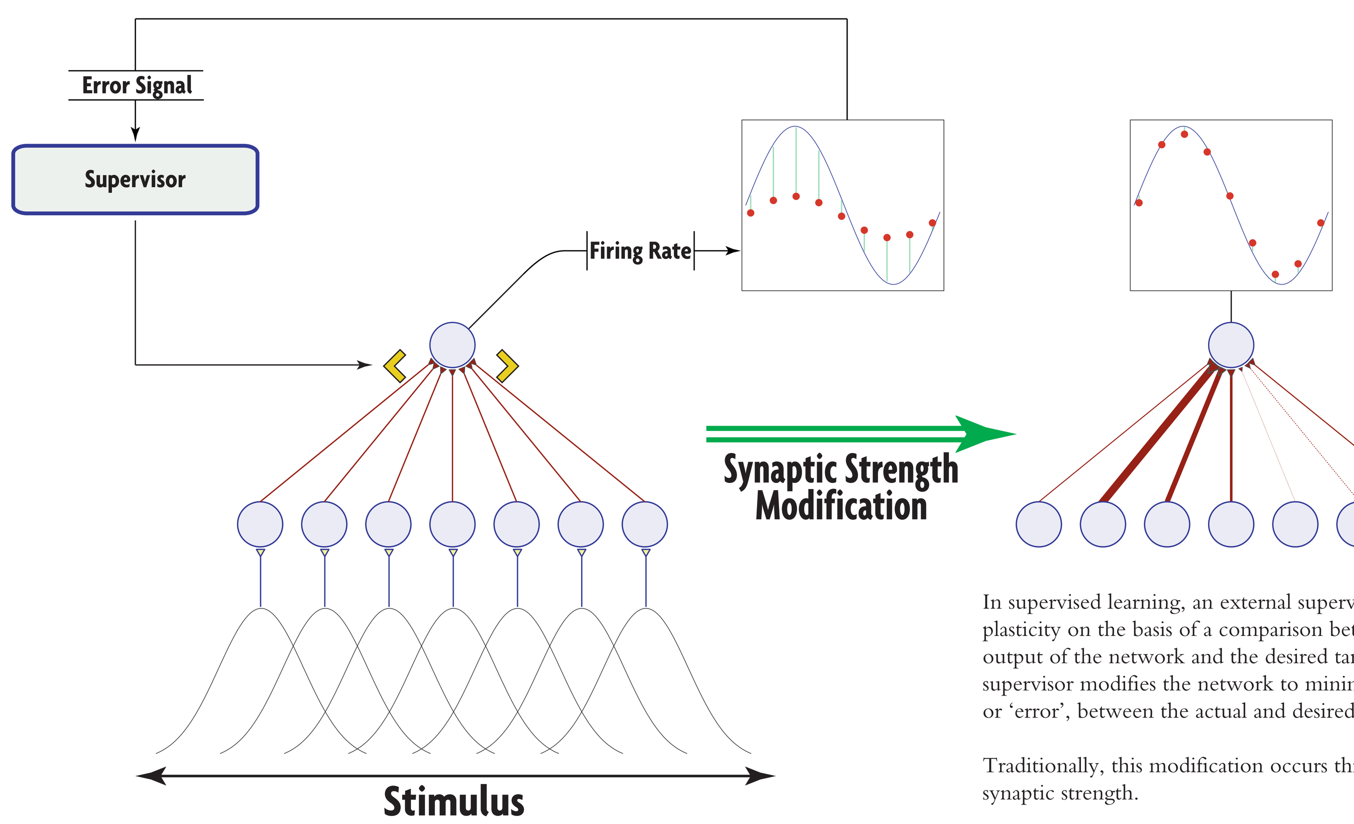
Function Approximation Learning



Function approximation is a standard neural network paradigm for modeling learning processes. In it, a stimulus characterized by a single parameter (the 'stimulus value') drives a network to generate a firing rate in an output unit which matches a desired target function of that parameter.

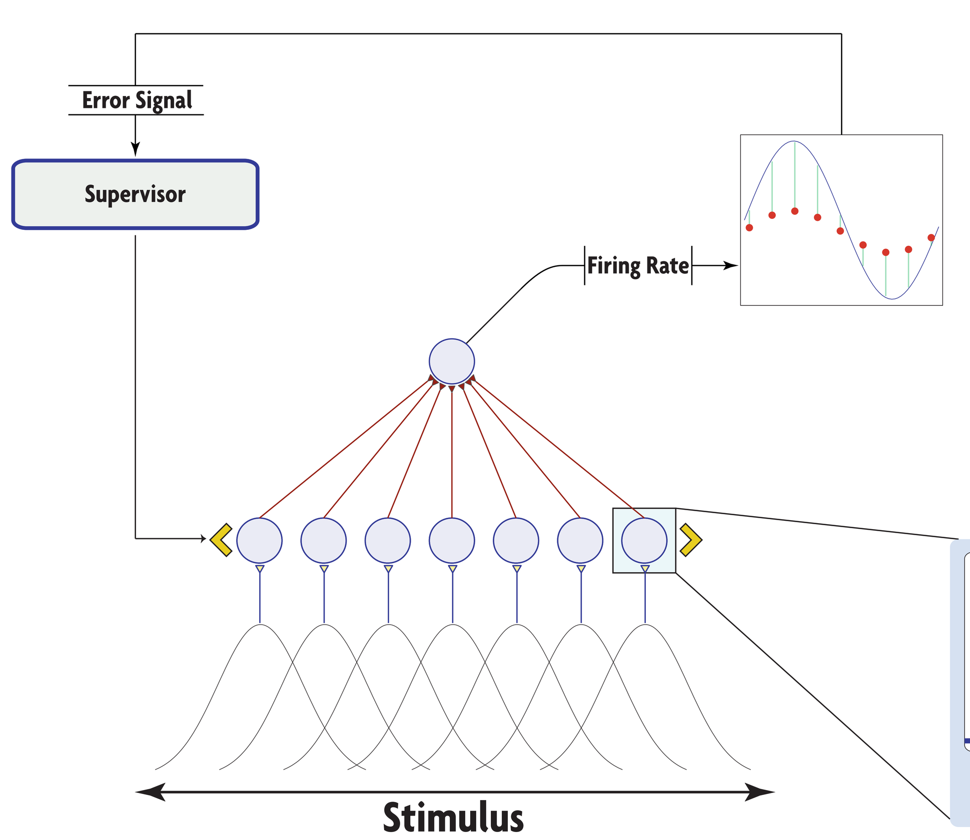
Traditional Supervised Learning



In supervised learning, an external supervisor unit controls plasticity on the basis of a comparison between the actual output of the network and the desired target function. The supervisor modifies the network to minimize the discrepancy, or 'error', between the actual and desired outputs.

Traditionally, this modification occurs through changes in synaptic strength.

Response Modulation-based Learning

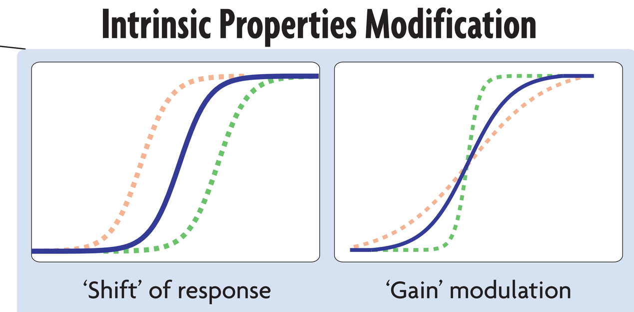


A major drawback of the traditional approach is the lack of a plausible mechanism by which error signals generated by the supervisor could reach individual synapses to guide their modification.

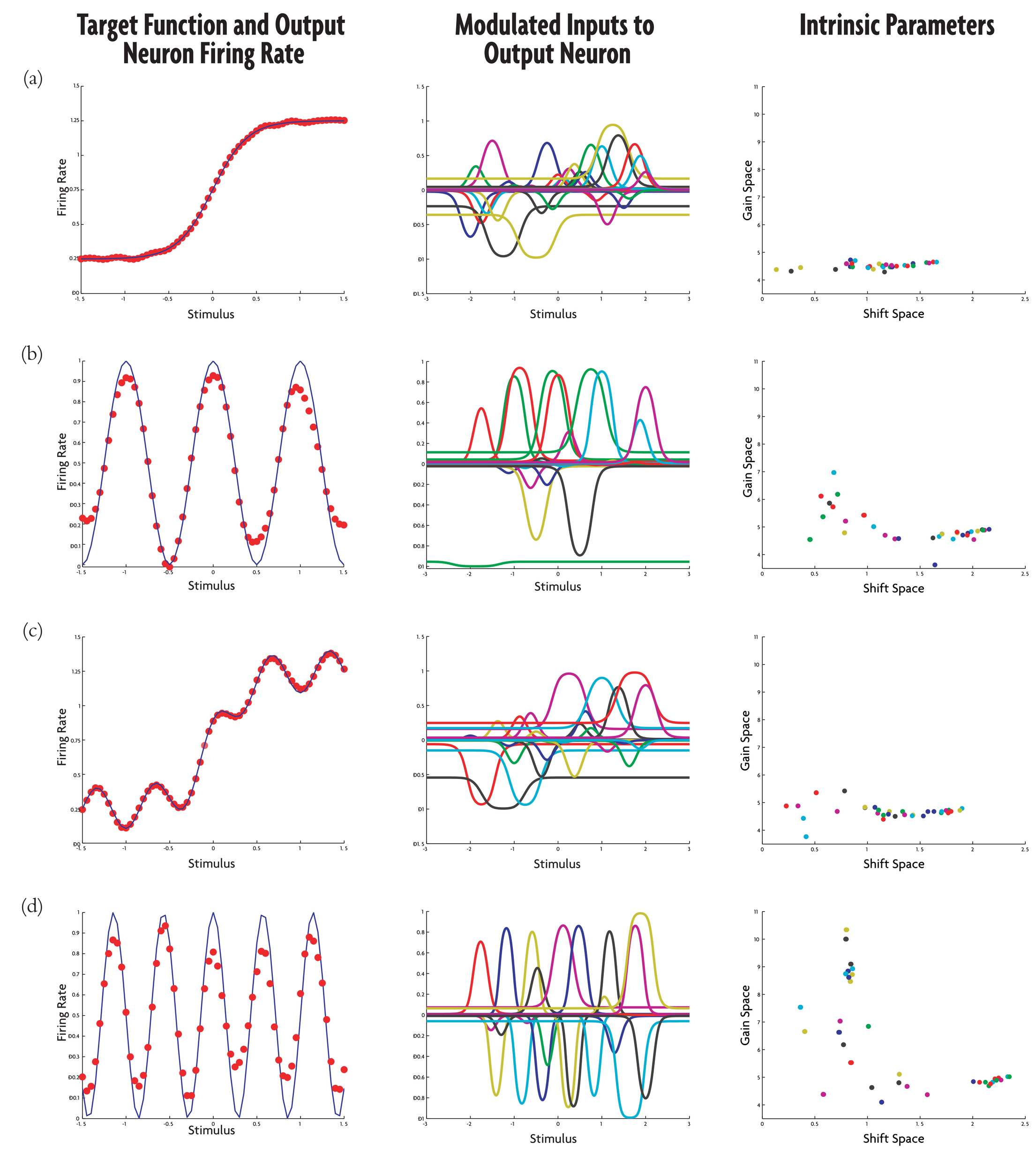
In this study, the supervisor modifies intrinsic neuronal response properties, rather than synaptic strengths, to guide learning.

Recent work (Chance et al., 2002) has shown that the response properties of individual neurons can be modified through changes in the level and balance of their excitatory and inhibitory inputs. This provides a pathway by which supervisor error signals can reach elements of a network to guide its modification during learning.

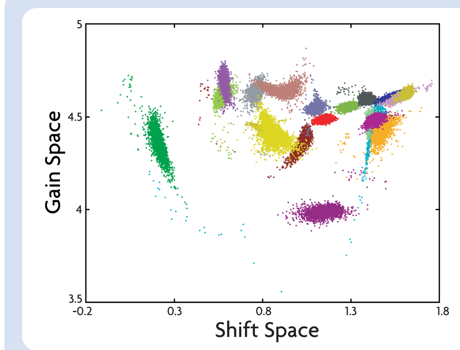
Intrinsic Properties Modification



Generality & Interference Effects



Uniqueness

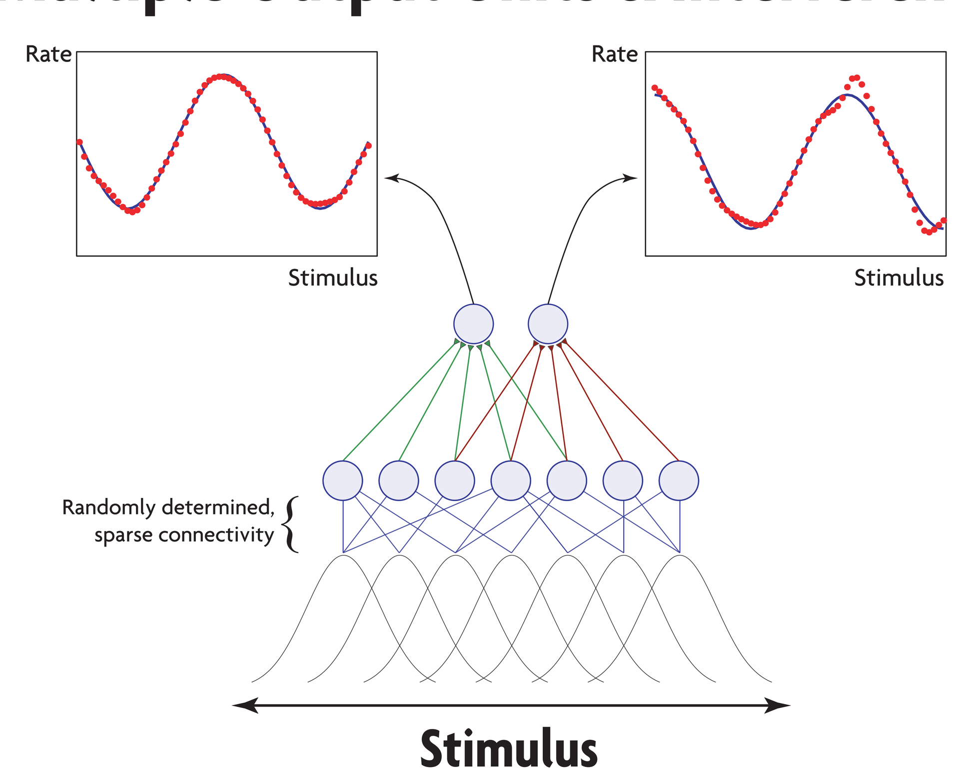


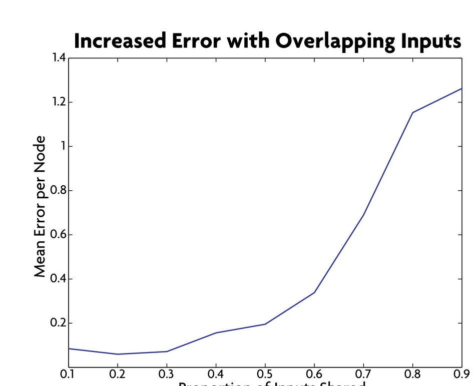
When the same function is learned repeatedly, the final shift & gain values for each input neuron are not identical. However, they do cluster over a similar range of values.

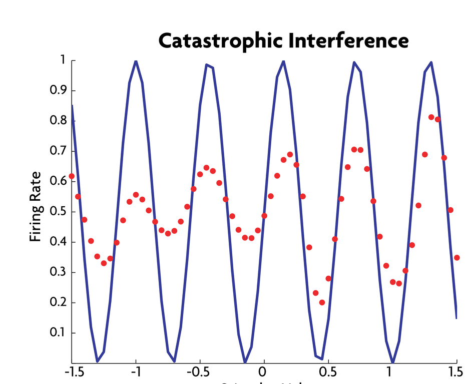
Supervised learning through intrinsic property-modulation is capable of fitting a variety of target functions. Here we see the network's approximation of:

a) A sigmoid function
b) A simple sinusoid
c) A linear combination of (a) and (b)
d) A sinusoid approaching the sampling frequency of the array of gaussian inputs.

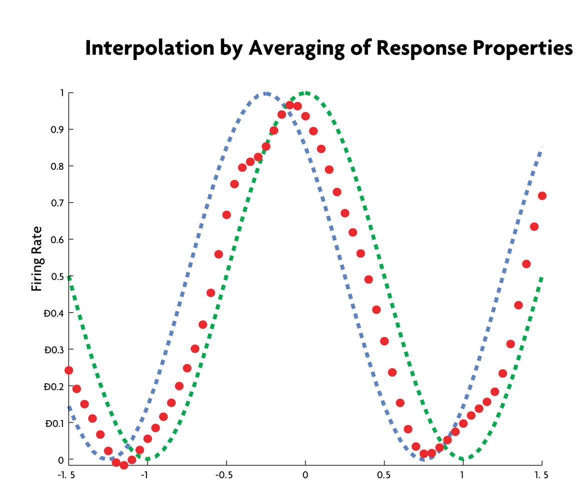
Multiple Output Units & Interference

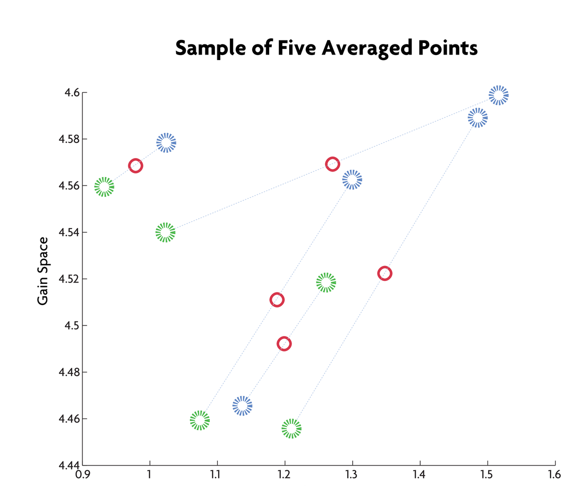




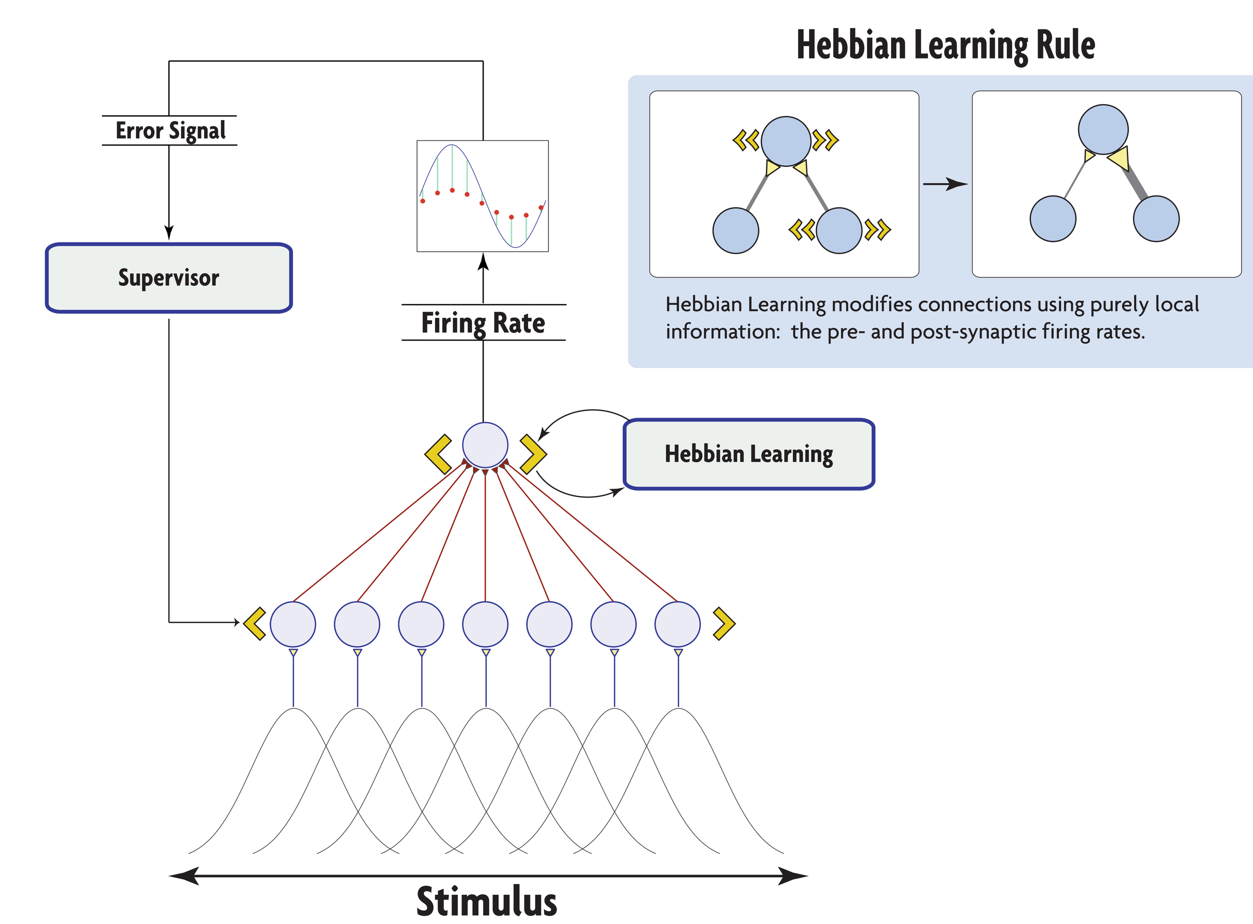


Interpolation Between Learned States





Transfer from Intrinsic Properties to Synapses

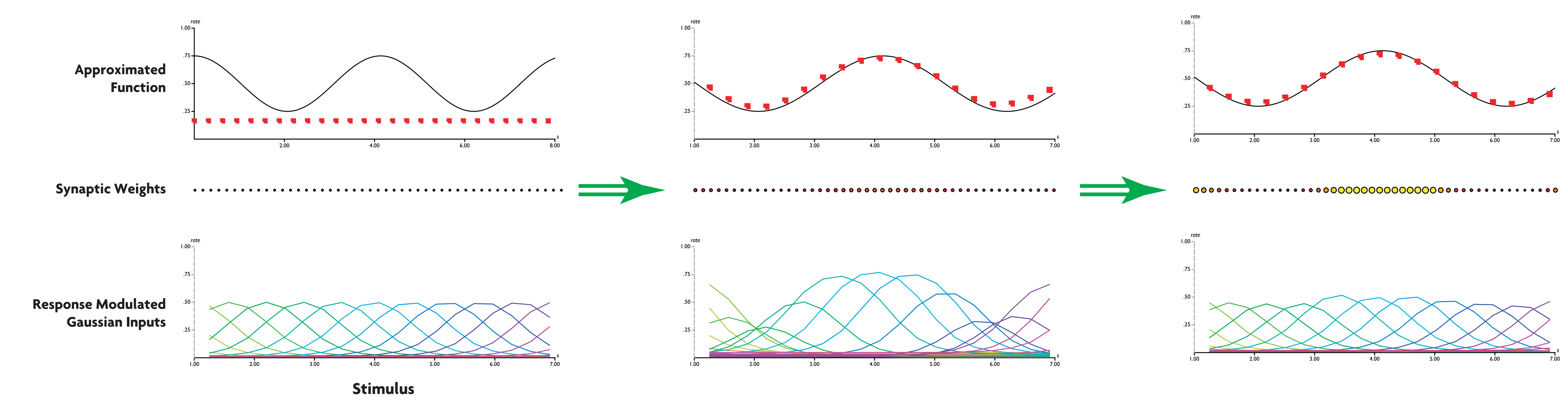


We have shown that the supervisor can induce the network to perform its task. However in the absence of the supervisor-driven modulation, nothing in the network has actually changed, and it will behave just as it did before any 'learning' took place.

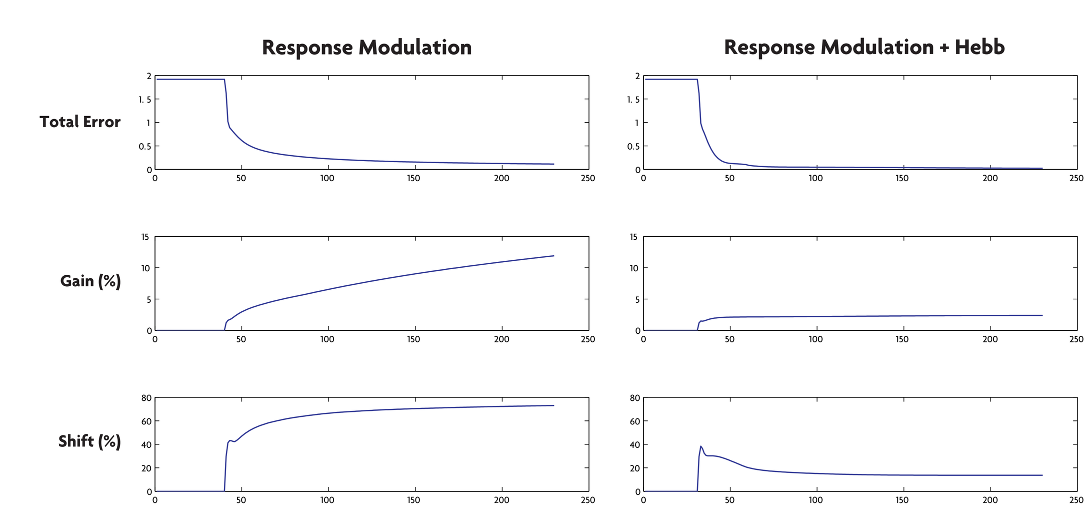
To be fully equivalent to the traditional network learning approach, the task must somehow be transferred to longer-term storage in the synapses.

When a simple hebbian synaptic plasticity rule is added to the network model, the information required by the network to perform the function approximation task is automatically transferred from the supervisor to the synapses through the modulation of intrinsic properties. Although the task could not have been learned using hebbian learning by itself, this two-step process results in a network that can perform the task through properly tuned synaptic strengths, even when the supervisory modulatory signal is removed.

Response Modulation Learning with Hebbian Synapses



Removing the Modulation Signal



Conclusions

This work addresses the long-standing problem of inducing a neural network to exhibit a desired behavior, and then modifying its synaptic connectivity to reproduce the behavior in the future. However, unlike traditional approaches there is no need for an implausible mechanism to propagate the error signal to the synapses.

Instead the supervisor's actions are realized entirely through ordinary patterns of excitation and inhibition, and the synaptic modification occurs through simple, unsupervised hebbian learning.

We have demonstrated that the Response Modulation approach is capable of approximating a broad variety of functions, and that prior learning can be generalized to adapt to previously-unseen examples.

Finally, we have shown that while modifying individual neurons' properties instead of their synapses does deprive the network of some flexibility, the degree of interference is manageable given properly sparse connectivity within the inputs.

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