The Extreme Learning Machine as a model to study pattern discrimination in insect brains

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The Extreme Learning Machine (ELM) is an approach for machine learning based on an artificial neural network with one hidden layer (Huang et al., 2006). In the ELM, weights and biases to the hidden layer are initialized randomly and not modified afterwards. During training, the output weights are then derived using a least-squares approach, which makes ELM training extremely fast compared to backpropagation algorithms, while delivering comparable performance.

The concept of the ELM hidden layer – providing a large number of random transforms of the input from which a mapping to the correct output is derived – shares a certain similarity to the concept of the olfactory pathway in the insect brain. A characteristic feature of this system is the huge fan-out of connections from the primary relay station, the antennal lobe, to the multimodal integration center, the mushroom body (MB). For example, in *Drosophila*, information from about 50 input channels fans out to about 2500 mushroom body neurons. Those connections are thought to be made randomly, and it has been shown that random connectivity maximizes the coding capacity of the system (Jortner et al., 2007). The difference to the ELM is that each neuron in the MB receives input from random 50 % of input neurons, while the ELM has all-to-all connectivity from the input to the hidden layer.

In this study, our aim was to use the ELM as a model to analyze pattern discrimination in a fan-out architecture like found in the insect brain. To this end, we analyzed two aspects of the olfactory pathway in the MB. First, we checked whether degrading the connectivity between input and hidden layer to 50 % as found in the MB affected classification performance. Second, as odors in the MB are thought to be represented by single input spikes locked mainly to odor onset, continuous value coding with firing rates becomes unlikely. We therefore changed the representation of the features to discrete values in {-1,0,1}. We found that neither degrading connectivity to 50 % nor discretization of features had a negative impact on the performance of the ELM.

Our results suggest that a fan-out structure with random connectivity as found in the insect olfactory system is capable of learning complex data spaces with accurate classification comparable to state-of-the-art machine learning algorithms.

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References

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