Evolving Neural Networks - Evolutionary Algorithms and Self-Organising Maps

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1. Introduction

Classical artificial neural networks have helped improve predictions in the stock market, refine understanding of the biological brain, advance voice recognition systems and furthered research & solutions into many other areas. Yet despite these breakthroughs classical artificial neural networks have themselves shown limitations of their abilities, particularly in the face of very complex data and through un-solvable obstacles in their core design.

In the mid 1970's a Finnish academic decided to investigate ways of improving neural network research for use in with data where classical neural networks had proved inadequate (Kohonen, 1995). His work lead to the 1981 publication of the Self-Organising Map.

Though the Self-Organising Map has helped further research involving neural networks, it too has been shown to have obstacles that bring about limitations in its uses. These predominantly focus around the following:

Correct Classification Classically, the only way to be assured that the Self-Organising Map has correctly learned the inputted data is through human visual inspection of its output.

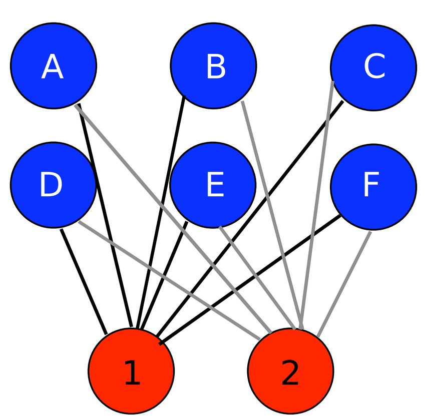
Correct Parameter Settings Locating the ideal parameter settings for the Self-Organising Map can be as difficult as the proverbial needle in a haystack, with trial-and-error leading the way to finding the correct settings for the parameters.

Previous research into these problems has focused on tackling one of them (and sometimes a subset of one of them) at a time. **The goal behind this current work is to bring some of these solutions together in order to determine if they *can* work together and whether such a collaboration brings benefits.**

2. Neural Networks

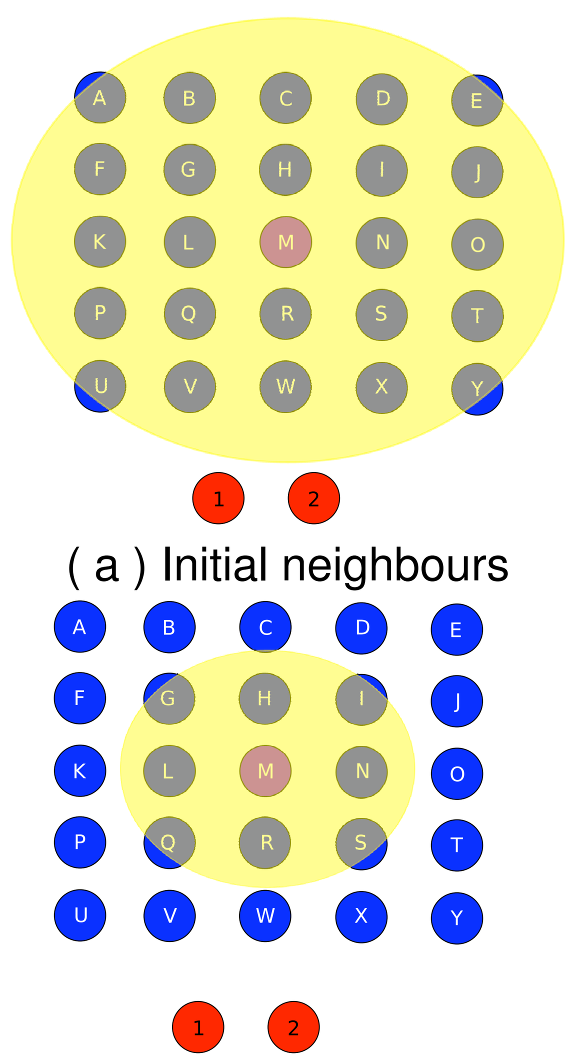
Briefly, artificial neural networks (ANNs) are based on theories developed from the observed behaviour of biological neurons. Inputted data 'stimulate' various artificial neurons in the network that have values close to that of the inputted data, this allows neural networks to sort data into regions or patterns. Classical neural networks focus on 'mapping' many input nodes onto few output nodes, however highly complex data (such as visual data) often cannot be 'mapped' by such a configuration.

Self-Organising Maps (SOMs) combat this problem by using a 'lattice' of artificial neurons where each neuron acts as an output, the neurons are not interconnected, but are linked to all inputs (see figure 1) and the neuron that matches the input data best 'responds' to it. This allows multi-dimension data to be 'classified' by two (and sometimes one) dimension of nodes.



3. Combating Classification Weakness

One of the observed weaknesses of the SOM method is that similar data may not be close to one another in the SOM lattice because the nodes they match best maybe far apart. Classically the SOM method has dealt with this by having the best matching node 'influence' the parameter values of its neighbours. This begins with all nodes in the lattice and gradually reduces to no neighbours through a single 'decay' value for the whole SOM (as shown in figure 2).



(a) Initial neighbours

(b) Mid-execution neighbours

Figure 2: *Neighbourhood size decay*

Researcher Kimmo Kiviluoto (Kiviluoto, 1996) recognised that the single 'neighbourhood decay' parameter may not be sufficient in bringing similar data closer together and so replaced the method with one where each node determined its own 'decay' measure which it could 'reset' as when nodes were found to be 'too far apart'. This method is named "AdSOM".

4. Evolutionary Algorithms

Evolutionary algorithms, and in particular genetic algorithms, are based on research from the field of evolution theory pioneered by Charles Darwin. The idea behind the algorithms is to use various evolution theory methods to find the best values in some search space. This is achieved through:

- Generating many individuals of randomly chosen parameters
- Calculating the fitness of each individual based on it position in the search space
- 'Mating' two of the fittest individuals to create new potentially better offspring
- Mutating the offspring to maximise variety
- Selecting the best individuals to survive into the next generation

5. Combining Research

Because evolutionary algorithms are adept at finding values that return the maximum benefit from a myriad of possibilities, they can be used in partnership with SOMs to solve the problem of finding the correct parameter settings for some inputted data. In this partnership the SOM acts as the evolutionary algorithm's 'fitness function', which calculates the fitness of an individual. Figure 3 depicts this collaboration in more detail.

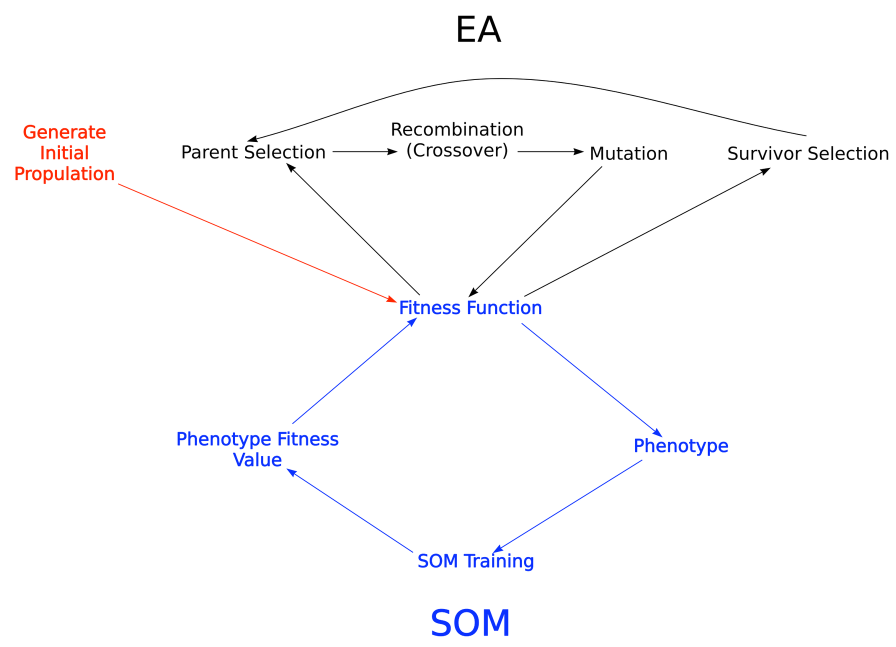


Figure 3: *Evolutionary algorithm & SOM*

6. Results

Figure 4 depicts the results of comparing a SOM implementation that includes the AdSOM method with an implementation of the classical SOM algorithm. Both tests use the same number of artificial neurons in the SOM lattice, as well as run for the same number of iterations and use the same learning rate that was found to be optimal by the genetic algorithm after numerous runs.

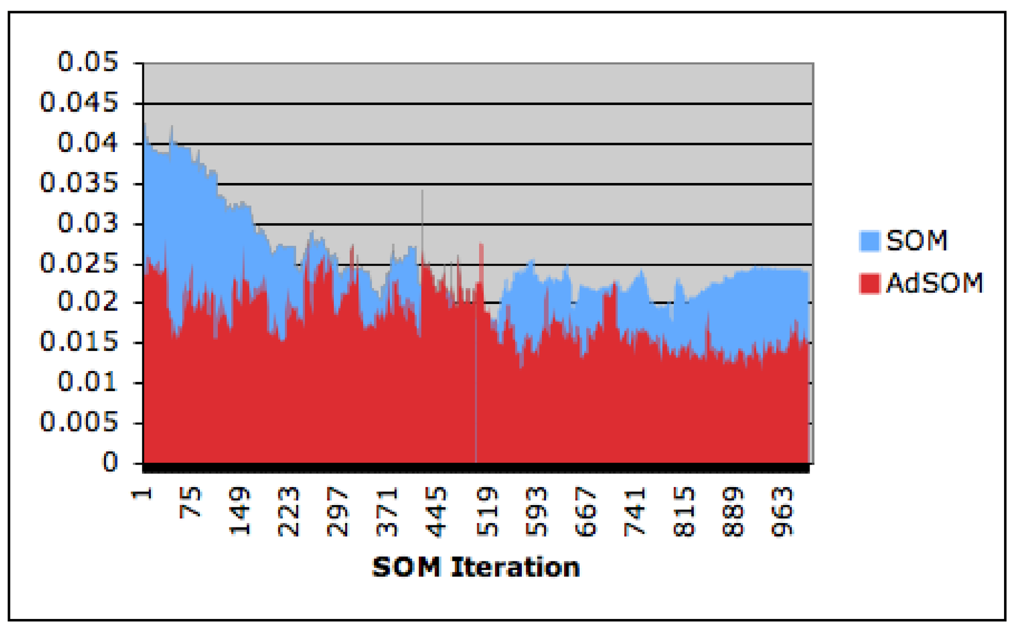


Figure 4: *Evolutionary algorithm & SOM*

It is clear from these results that the AdSOM method performs well.

References

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Kohonen, T. (1995). *Self-Organizing Maps*, Volume 30 of *Springer Series in Information Services*. Heidelberg, Germany: Springer-Verlag.