The University of Reading

Dynamic Neural Networks

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by
Robert Ian William Lang

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Abstract

Artificial Neural Network (ANN) classification in non-stationary environments is a non-trivial problem as ANNs operate on fixed training sets and thus classify inaccurately in such applications. A Dynamic Neural Network (DNN) is here defined as a Neural Network that can alter its own topology to accept perpetual novelty in a non-stationary signal space. One such network is Fritzke's GNG-U algorithm.

A novel DNN called the Plastic Self Organising Map (PSOM), an extension to Kohonen's Self Organising Map (SOM) is presented. The PSOM is a graph structure, constructed online from the temporal and spatial properties of the input space. In tests, the PSOM is shown to classify accurately on a number of non-stationary environments, perpetually accepting new classes and forgetting old patterns. The effects of the parameters on the network's operation are investigated and the PSOM is shown to be robust in the selection of its parameters. The PSOM is improved with the Extended Plastic Self Organising Map (EPSOM), which requires fewer parameters required to initialise the network. A comparison was made with Fritzke's GNG-U algorithm and it is found that GNG-U was slower but more accurately represented the topology of the input space.

A novel algorithm called the Temporal Plastic Self Organising Map (TPSOM) is presented, which is an output graph consisting of a Markov chain that can be used to predict the next input state. This algorithm alters the semantics of the PSOM's links. The TPSOM is shown to classify accurately on a static Markov chain and a dynamic Markov chain modelled by switching from one static Markov chain to another.

All the novel algorithms are tested on a real world radar data set. This is an example of a non-stationary system as a class disappears during the length of dataset and another class appears. The PSOM and EPSOM are able to classify while keeping a bounded topology. As the radar data set did not have ordered structure, the TPSOM does not produce a meaningful structure. The TPSOM is also shown to represent some of the statistical properties of a piece of plain English text.

Dedicated to Mum and Dad

The hotel that never closed,

The bank that never refused,

The support that never faltered.

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