NEURO SYMBOLIC INTEGRATION AND AGENT BASED MODELLING

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Abstract: Logic program and neural networks are two important perspectives in artificial intelligence. The major domain of neuro-symbolic integration is designed by the theory are usually known as deductive systems which less such elements of human reasoning as adaptation, learning and self-organisation. Meanwhile, neural networks, known as a mathematical model of neurons in the human brain, and have various abilities, and moreover, they also provide parallel computations and therefore can perform some calculations quicker than classical learning algorithms. Hopfield network is a feedback (recurrent) neural network, consisting of a set of N interconnected neurons which each neurons are linked to all others in all the directions. It has synaptic strength pattern which involve Lyapunov function E (energy function) for energy minimization events. It operates as content addressable memory systems with binary or bipolar threshold units.

On the other hand logic connected with true and false. A bi-direction mapping between propositional logic formulas and Lyapunov energy functions of a symmetric neural networks had been introduced researchers known as neuro symbolic integration. It involves around propositional Horn clauses with learning capability of the Hopfield network which enable the network to hunt for the good solutions, when the corresponding clauses in the logic program are given, with the corresponding solutions may change as new clauses are added.

We are motivated to develop agent based modelling (ABM) for integration mean field theory for doing logic programming in the Hopfield network. An ABM is a new computational modelling venture which is an analysing systems that representing the 'agents' that involving and simulating of their interactions. Their attributes and behaviours will be classified together through their interactions to become a scale.

Keywords: Logic program, neural networks, mean field theory, agent based modelling.

Introduction: Neural network is a parallel processing network which generated with simulating the image intuitive thinking of human, on the basis of the research of biological neural network, according to the features of biological neurons (such as our brain) and neural network and by simplifying, summarizing and refining [1-3]. It uses the idea of non-linear mapping, the method of parallel processing and the structure of the neural network itself to express the associated knowledge of input and output.

The Hopfield neural network [4] is a simple recurrent network which can work as an efficient associative memory, and it can store certain memories in a manner rather similar to the brain. Wan Abdullah [5] proposed a method of doing logic program on a Hopfield network where optimization of logical inconsistency is carried out by the network after the connection strengths are defined from the logic program; the network relaxes to neural states which are models (i.e. viable logical interpretations) for the corresponding logic program. Type of learning implemented in this network is known as Wan Abdullah's learning or Direct Learning Rule. The connection weights are determined by comparing the cost function with energy function of the network. The advantages by using Wan Abdullah's method are it can revolves around propositional Horn clauses and learning ability of the Hopfield network and hunts for the best solutions, given the clauses in the logic program, and the corresponding solutions may change as new clauses added.

Logic Programming On A Hopfield Network: In this section we will discussed briefly some important concepts related in doing logic programming in Hopfield network by using program clauses. Take into consideration a system consists of *N* formal neurons and each of represented by an Ising variable $S_i(t), (i = 1, 2, ...N)$. Neurons then are bipolar, $S_i \in \{-1, 1\}$, follow the dynamics $S_i \rightarrow \mathrm{sgn}(h_i)$, where the field, $h_i = \sum_j J_{ij}^{(2)} S_j + J_i^{(1)}$, *i* and *j* running over all neurons *N*, $J_{ij}^{(2)}$ is the connection strength from neuron *j* to neuron *i,* and $-J_i$ is a fixed bias (negative of the threshold) applied externally to neuron i. Hence, the neuron modifies its state S_i; according to Mc-Culloch Updating Rule.

The connections are symmetric and zero-diagonal, $J_{ij}^{(2)} = J_{ji}^{(2)}$, $J_{ii}^{(2)} = 0$, which allows one to write a Lyapunov or energy function,

$$E = -\frac{1}{2} \sum_i \sum_j J_{ij}^{(2)} S_i S_j - \sum_i J_i^{(1)} S_i \tag{1}$$

which monotonically decreases with the dynamics. The dynamics thus allows the handling of combinatorial optimization problems, whereby neurons are mapped onto the combinatorial variables and the cost function is equated to the energy function of the optimization problem.

The two-connection model can be generalized to include higher order connections. This modifies the "local field" into

$$h_i = ... + \sum_j \sum_k J_{ijk}^{(3)} S_j S_k + \sum_j J_{ij}^{(2)} S_j + J_i^{(1)} \tag{2}$$

where "....." denotes higher orders connections, and an energy function can be written as follows:

$$E = ... - \frac{1}{3} \sum_i \sum_j \sum_k J_{ijk}^{(3)} S_i S_j S_k - \frac{1}{2} \sum_i \sum_j J_{ij}^{(2)} S_i S_j - \sum_i J_i^{(1)} S_i \tag{3}$$

provided that $J_{ijk}^{(3)} = J_{[ijk]}^{(3)}$ for *i, j, k* distinct, with [...] denoting permutations in cyclic order, and $J_{ijk}^{(3)} = 0$ for any *i, j, k* equal. The updating rule maintains

$$S_i(t+1) = \mathrm{sgn}[h_i(t)] \qquad (4)$$

In logic programming, a set of Horn clauses which are logic clauses of the form $A \leftarrow B_1, B_2, \ldots, B_n$ where the arrow is read as "if" and the commas "and", is given and the aim is to find 'models' corresponding to the given logic program. The model here refers to a setoff interpretation which satisfies the logical clauses.
Logic programming is the use of mathematical logic for computer programming. Thus, higher order Hopfield network had carried out in logic programming model [6, 7].

Mean Field Theory: Mean Field Theory (MFT) is a staple paradigm, widely used in solving dynamic systems and problems in various field of sciences. Specifically, MFT also been applied to solve dynamic systems in physics, medicine, engineering, optics and other fields. There are a plethora of literature discussing on the development and application of MFT especially in improving the dynamic system computation. The work of Peter and Anderson [8] has introduced the MFT equations in regulating the neuron activation mechanism. From that extend, a prolific number of research has transformed the MFT into a very versatile method that can be blended with other algorithms to tackle the dynamic system computation [9].

In stochastic neurons, the firing mechanism is described by a probabilistic rule. In any event, let $< s_j >$ denote the average (mean) of s_j .The state of neuron j is described by the probabilistic rule:

$$S_j = \begin{cases} +1 & \text{with probability } P(h_j) \\ -1 & \text{with probability } 1- P(h_j) \end{cases}$$

where

$$P(h_j) = \frac{1}{1+\exp(-h_j / T)}$$

where T is the operating temperature. Hence the average $< s_j >$ expressed for some specified value of the induced local field s_j as follows:

$$\langle s_j \rangle = (+1)P(h_j) + (-1)\left[1 - P(h_j)\right] = 2P(h_j) - 1 = tanh(h_j / 2T)$$

The basic idea of mean-field approximation is to replace the actual fluctuating induced local field h_j for each neuron j in the network by its average $< h_j >$, shown by

$$\langle h_j \rangle = \left(\left\langle \sum_i w_{ji} s_i \right\rangle \right) = \sum_i w_{ji} \langle s_i \rangle$$

Accordingly, the average state $< s_j >$ computed for neuron j embedded in a stochastic machine made up of a total of N neurons, just as in the Equation below for a single stochastic neuron,

$$< s_i > = tanh\left(\frac{1}{2T} h_j\right) = tanh\left(\frac{1}{2T} < h_j >\right) = \tanh \frac{1}{2T} \sum_i w_{ji} < s_i >$$

From derivation of above equation, the mean-field approximation is stated as:
The average of some function of a random variable is approximated as the function of the average of that random variable.

Agent Based Modelling: Firstly, a simulator of Hopfield networks that using a conventional computer had been created with a new network design or store a new set of memories. We used NETLOGO version 6.0 as the platform. It will be easier for the programmer to modify the program and store a new set of data. Thus, an agent based modelling had designed for the user to run the simulator.

Moreover, agent-based Modelling (ABM) which also called individual-based modelling is a new computational modelling paradigm in Hopfield network. Their attributes and behaviours will be grouped together through their interactions to become a scale. Programmer can design ABM in Netlogo by using button, input, output, slides and other functions that make ABM easier to understand and to be user friendly. In addition, ABM reveals the appearance of the systems from low to high level outcomes. Thus, it make improvement by surpassing the traditional modelling limitations such as allowing agent learning and adaption, limited knowledge and access to information. So, by using this approach we can get a clear visualization on procedures of doing logic programming in Hopfield network.

Results And Discussion: We will discuss the performance of the models developed by using global minima ratio. From the 1 it can be observed that overall for Lower Order Network the three methods also perform quite good, more than 80% are global solutions. This is because the network complexities still low and the neurons able to relax smoothly to global solutions. Since average local field is used to update the neurons state in MFT so the probability for the neurons to get stuck in local minima becomes less. The neurons flipping and fluctuation can be minimized by using averaging term in the MFT algorithm. Furthermore, by ignoring the neurons fluctuation, the noise in the network also can be avoided.

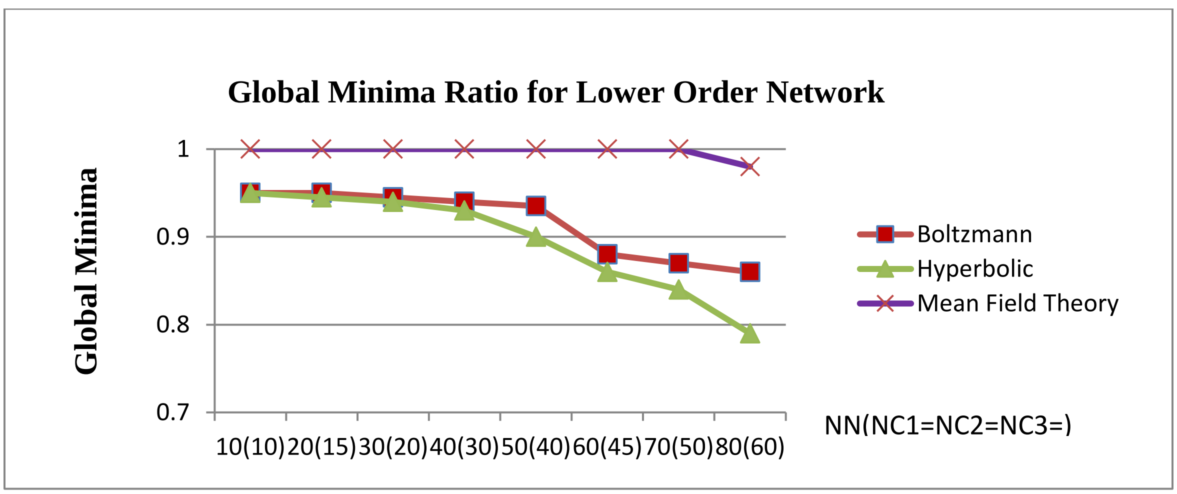

Figure 1: Global Minima Ratio For (Number of clauses=1(NC1), Number of clauses =2(NC2), Number of clauses =3(NC3))

BM seems to perform better that HTAF. This is due to the simulated annealing procedure carried out by the BM where the neurons are forced to jump the energy barriers to relax into global solutions by increasing the network temperature. However, when the network complexity increased, the performance using BM seems to decrease.

Conclusion: In this paper, we had developed agent based modeling to carry out logic programming in Hopfield network by using NETLOGO as a platform. From the study we found that the ability of MFT in doing logic program on Hopfield network is good. It provides a better result in term of hamming distances. Although ABMs develop model the process of doing logic programming in Hopfield network are quite efficient, the system still facing oscillation problem when involving in high complexity of systems that larger than third order clauses.

Acknowledgment: The research is financed by USM GOT grant (1001/PMATHS/823032) and Universiti Sains Malaysia.

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