Spiking Networks as Non Local Cellular Automata

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Tofara Moyo

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1st Tofara Moyo
Bulawayo , Zimbabwe
tofara@cwvermaak.com, Mazusa AI

***Abstract*—In this paper, we propose a novel regularisation method for spiking neural networks. We note the similarities of a spiking network to a non local cellular automaton and derive a rule for its connections that must be learnt. This rule results in the activations of the network forming a grammar. We also view each state of the spiking network as a node on a hyper graph and show that we can generalise by simply sending the never before seen acivations presented at a novel state or situation, to the next activations that the grammars rule would have them move to. We also demonstrate that hierarchical planning may be achieved by the particular grammar we choose.**

I. Introduction

A. Non local and Local Cellular Automata

A cellular automaton is a type of graph, where the nodes are modeled as cells on a grid. They can have local connections, in which case each cell is connected only to those adjacent to it. Giving rise to the local cellular automaton. Or they could have non local connections, where a cell may be connected to another at some other part of the grid other than adjacent to it. In this case we have a non local cellular automaton.

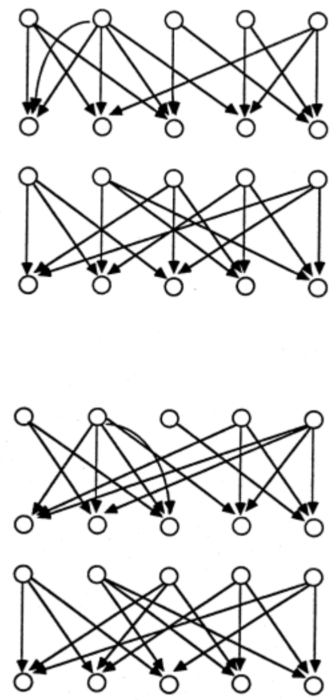
A signal may move across a cellular automaton from the initial inputs (selection of nodes), that travels along the graph selecting nodes for attention. Complex patterns of activations may occur.

Considering a system with N components, each of them has a state value x_i at time t (i = (1,2,3...)). A three input (k = 3) rule $f(.)$ can be specified in the form: x_i^{t+1}= $f(x^t_{j1(i)}(x^t_{j2(i)}(x^t_{j3(i)})$ where $(j1)$,$(j2)$,$(j3)$ are somehow chosen from among the N components.

The wiring scheme for the local and non local automata , i.e. how $j1$,$j2$,$j3$, are chosen, is as follows:

1. Local connection:$j1$=$i-1$, $j2$=i,$j3$= $i+1$. The first input is the left neighbour, the second is the site itself and the third is the right neighbour.

2.Non local connections:$j1$,$j2$,$j3$ may be chosen at random. Here the degeneracy of inputs might happen whenever two or three inputs are the same.



An interpretation of a cellular automaton has us view each presentation of the grid (the currently attended to nodes at that time step)as a node. It follows then that a local cellular automaton can be viewed in some sense as a series of nodes on a line. Where each node is indexed by the presentation of the grid when the cellular automaton is attending to the node.

A non local cellular automaton at this level of abstraction would best be seen as yet another graph, with nodes indexed by the corresponding currently firing nodes on the grid.

In the case of the non local automaton, were we to select random connections for it, the attended to nodes on its hyper graph would move around the graph from node to node randomly. Were we to select a rule for the connections, the hyper graph of the non local cellular automaton would have the nodes attended to in a structured way, with a related rule.

II. Spiking networks

Spiking neural networks (SNNs) offer a perspective on machine learning different than that of traditional artificial neural networks (ANNs): SNNs encode data in a series of discrete time spikes, modeled after the action potentials created by neurons in biological brains. The original development of ANNs was also inspired by the human brain, which consists of nearly 100 billion neurons, each of which can have up to 15,000 synapses.

Spiking neural networks are graphs as are all networks. The graph that they most similarly represent is a non local cellular automaton. That is because nodes in the spiking network may have random connections, or according to a rule that doesnt connect adjacent neurons. The connections of it would be a choice of the designer of the spiking neural network. An open area of research is to find the optimal way of connecting nodes in a spiking neural network , to enable it to have the same functionality as the human brain. I .e. posses long and short term memory, processing capabilities and so on.

As mentioned, a spiking neural network may be viewed as a non local cellular automaton. But this is not a statement about the physical connections it has as much as a statement for the disposition for neurons to fire after each other. The first is fixed at design, while the second is learnt.

These learnt connections force the spiking network to present activations that achieve what the network was trained to do. At the cellular automaton abstraction of connections we find that it also learns a hyper graph of sequences of firing node presentations that allow it to function.

We know that if this hyper graph were more structured and rule based then it would enable quicker learning and greater generalisation.

To this end the practise of regularisation and its methods help structure this hyper graph. In the next section we introduce a method of regularisation that would allow the network to perform better.

III. Musical keyboards are non local cellular automata

In the paper "Structuring Concept Space with the Musical Circle of Fifths by Utilizing Music Grammar Based Activations", Moyo et al note that the sequence of notes and chords that form a piano piece on a musical keyboard can be viewed as a non local cellular automaton. The rules for connecting node being found in music theory.

They first note the similarities between a piano piece and a spiking neural network The former consists of nodes on a keyboard that are played concurrently with each other (as in a chord) or played in sequence (as in a melody), while the latter (spiking neural network) consists similarly of nodes that either activate concurrently or in a sequence.

While a spiking neural network learns its connections through training, a piano piece is designed. As for the hyper graph of each. While spiking networks use various regularisation techniques used to make it regular, the designer of the piano piece utilises the rules of music theory.

Noting these similarities we decided to model the spiking network as a piano piece such that we could regularise it with music theory principles. These principles hinge deeply on the musical circle of fifths and the musical circle of fourths which are built out of the generators for the group D12. Not surprising as the western chromatic scale has 12 notes.

But what is the main object that music theory chases? It is in maximising the consonance of chord and melody choices in one interpretation. Musical scales, consist of masks placed on the chromatic scale , where only a selection of notes from the chromatic scale are considered when composing. Scales can be seen as highly consonant sub spaces in musical pitch interval space.

That gives us a way to use the whole of musical theory, even the parts that are not fully developed as complete, to regularise our music grammar based spiking neural network. What we need to do is to treat the nodes in a layer of the spiking network as the keys on a musical keyboard by mapping them onto each other. Then running the network forward and recording the activations that occurred.

After viewing them as their music key doubles , we compute their perceptual consonance and use this value as a reward to reward the reward modulated spiking neural network.

IV. Discussion

We have set about regularising our spiking neural network with music theory. That way the activations on spiking network form a musical grammar instead of happen in an ad hoc manner determined through training.

This is biologically accurate. The brain uses its own type of grammar to regularise its activations. This means that the hyper graph it builds is highly regular, giving insights into why it is able to generalise and learn so easily.

A hyper graph built of a grammar enables faster learning and greater generalisation. It means that the hyper graph is highly regular and contains a simple rule for maximising external reward or learning an new thing.

In the case of our music grammar spiking network , we hypothesise that the optimal traversal of the hyper graph will be structured by the musical circle of fifths and fourths. In fact it can be seen that after an initial training phase , if one were to simply optimise this hyper graph for consonance without training for the main objective one would achieve better than example performance in that objective.

If this was a humanoid agent sent into the real world it would have a hyper graph that is indexed by the presentation of the active nodes, as well as probabilistically by the state.

If this agent was trained on an external reward, the question of what it should do next at each time step may boil down to what set of activations are a fifth or a fourth away from the currently activated neurons.

This agent would essentially have generalised well because it will have a simple rule for acting that works on all states and inputs. Moving along the circle of fifths or fourths in activations.

If the agent found itself performing sub optimally a simple fix would be to learn in the direction of maximising movement around these circles. This view abstracts away from particular tasks and finds a general rule to learn a new task given training on other tasks. An important part of generalisation.

Also it can be seen that upon being presented with a new challenge that it has never faced before , the agent may simply take the correspondingly never before seen set of activations and solve the task in a one shot manner by moving them along in steps that go with the musical circle of fifths or fourths.

This algorithm also benefits from causality. Since there is a higher probability for one particular state to be followed by another particular state , it follows that the activations will learn to correlate accurately. What solving the consonant reward function amounts to is next state prediction , which is also biologically accurate.

In particular this system encourages the agent to visit states that have the same symmetries as the music grammar it learns. since it is free to learn any particular grammar as long as it conforms to music theory, it has some flexibility in this , which is good.

On the other hand the states it must visit consecutively in order to encourage just the right activations to occur consecutively must have high amounts of the right symmetry. We speculate that that the agent will treat the state and its own actions as extensions of the policy that must also be regulated. Encouraging it to learn faster and faster as it directs itself to states optimal for learning.

Another advantage of this system is that an agent using such a policy will learn to plan hierarchically.

Hierarchical planning involves making a plan that will achieve its objective in the future. It involves breaking the task into stages that must each be completed in sequence or in parallel till the entire plan has been completed.

What we have to note first is that music consists of stages . A piano piece almost invariably involves moving around the keys in order to create suspense for an eventual movement of a fifth back to the original key you started with.

If we were to reward the connections in the agents policy for conforming to music theory, the passage of its activations would follow just such a trend. This is highly speculative but we believe that the agent may carry out its plan hierarchically by both a combination of associating its activations causally with the states of the environment as well as moving them along the circle of fifths.

V. Conclusion

We have discussed a method of regularising a spiking neural network that achieves even more. We viewed the set of activations that fire at each time step as the nodes of a hyper graph. The form of this hyper graph gaves us insights into how well the network learnt and can generalise.

Regularisation aims to put more structure in this hyper graph than is simply learnt without it. Our method structures the hyper graph by the circle of fifths and fourths found in music theory. That is because , once we map the nodes of a SNN to a musical keyboard, we encourage activations with high consonance, by calculating its value were they keys being played and using it as a reward for the network.

This may aid in hierarchical planning and generalisation. Generalisation would be that the network has learnt to solve its problems by moving the set of activations that occur when a problem is presented along the circle of fifths or fourths.

Even if it is a new problem and hence the set of activations firing were never met before, the agent may solve it in a one shot manner by simply moving those new activations in the direction along the circle of fifths or fourths.

This indexed hyper graph can be viewed as a type of tollumn eichenbaum machine. Where things in memory are stored along a hyper graph with a rule for traversal that is highly regular.

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