Sequential Processing in Neuroscience Inspired Models

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Abstract

In the past a variety of computational problems have been tackled with different neural network approaches. However, very little research has been done on a framework which connects neuroscience-oriented models with connectionist models and higher level symbolic processing. In this paper, we outline a framework which focuses on a hybrid integration of various neural and symbolic preference techniques in order to shed more light on how we may process higher level concepts, for instance for language processing based on concepts from neuroscience. It is a first hybrid framework which allows a link between various levels from neuroscience, connectionist Preference Moore machines and symbolic machines. Furthermore, we discuss a model of pulsed neural network for classification of natural language data.

1 Introduction

Recently, there has been some preliminary work integrating principles from neuroscience into computational models e.g. [Maass and Bishop, 1999, Thorpe et al., 1996, Wermter et al., 1999, Taylor, 1999, Denham and Denham, 1999]. Although neuroscience principles have helped to develop new computational models, the problems they address are still restricted, and they indicate that new evidence from cognitive neuroscience may help build more realistic brain-inspired computational frameworks.

In many ways there is a challenging distance between lower cognitive neuroscience and higher concepts like in language processing. Our approach attempts to go beyond the neural approaches that are normally utilized. Our approach is based on the processing found in the brain, integrates sequential machines at diverse levels both vertically and horizontally, and exploits recurrent and pulse neural networks for more neuron-like processing. It is envisaged that tasks like auditory processing, robust syntactic analysis or semantic classification could benefit especially from such processing.

The focus of this new approach here is to explore hybrid neural architectures, including techniques from cognitive neuroscience and neural computation in order to produce realistic computational neural models of language processes and complex cognitive operations. These models require the integration and consideration of significant amounts of knowledge on brain structure and information processing that has been collected by neuroscientists and cognitive scientists. Furthermore, it is important to determine which principles are critical for higher level functions like language processing. These models, while being able to perform complex language processing operations, can also create general notions on language and the brain, and identify the information requirements for extended models. However, we would like to note that our presented framework is not about interpretation of biological neural networks or neurobiological modeling. Our goal is rather to achieve computational advantages from the development of neuroscience-inspired models of artificial neural networks.

2 Preference Moore Machines

A Preference Moore machine can be seen as a computational machine which has possible links to higher level symbolic machines or lower level neuroscience-inspired concepts. For instance, a SRN network, a form of sequential connectionist network [Elman et al., 1996], is one type of a preference Moore machine and can be interpreted symbolically as finite state machines. It has been shown [Wermter, 2000a], that symbolic transducers can be extracted from SRNs using our preference framework. Each state and each output within this preference Moore machine was mapped towards the references of an n-dimensional space. That way, a symbolic transducer represented a higher, more abstract representation of the more detailed connectionist preference Moore machine.

A substantial part of the information being processed in artificial and biological neural networks is encoded in a distributed manner and is transferred, or sometimes temporally stored, as pulsed signals between neurons. Within a given time window, neurons fire, indicating activity with the density or with the particular temporal location of the spikes. Reading such information from real systems or manipulating it in artificial systems is a complex task that addresses many processing and representational problems. In previous work we have introduced preference-based processing [Wermter, 1999, Wermter, 2000b] and an interpretation of firing rate and pulse coding schemes [Panchev and Wermter, 2000]. Here we would like to extend this work substantially towards an interpretation of some more complex neural network representations of cognitive events. While usually the processing and representation in the brain are believed to be task-dependent, a common neural/symbolic interpretation of spatio-temporal neural code is possible and crucial for hybrid systems.

In the remaining part of this paper we will also illustrate some links of the preference framework to the neuroscience level. While in [Panchev and Wermter, 2000] we presented the concept of neural preferences on a single neuron level, here we would like to concentrate on more complex cortical functional structures associated with cognitive functions in the brain: cell assemblies.

3 Using Preferences at Symbolic, Connectionist, and Neuroscience Levels: Cell Assemblies as C-Preferences

The concept of a cell assembly was introduced as a functional and structural model for cortical processes and neuronal representations of external events [Hebb, 1949]. Hebb presented the idea that complex objects and stimuli, as well as more abstract entities like concepts, ideas and contextual relations in the brain are represented as simultaneous activation of large groups of neurons. Single cells can belong to different assemblies and the cells in one assembly are not necessarily close to each other. If, as a result of an external event, a sufficiently large subset of the cells in the assembly are stimulated, the whole assembly becomes

active and may sustain activity for some period of time even when the external event has disappeared.
Cell assemblies are a widely accepted paradigm for feature binding mechanisms in the brain. In many artificial neural networks, cell assemblies are explored as a model of associative memories [Palm, 1986, Fransén et al., 1994]. Different interpretations of the paradigm can serve as a concept of short or long term memory models. The concept of neural assemblies in combination with activity-dependent (spatio-temporal) Hebbian learning provides a paradigm for long term memory [Wennekers and Palm, 1999].
Many artificial neural network models of cell assemblies use a simple neuron as the elementary computational unit of the network. However, there are several models of associative memories with spiking neurons that use models of cortical columns as functional units [Fransén and Lansner, 1998]. Although in both approaches a neuron or column represents a single feature, there are different interpretations of the behavior of that unit. In the interpretation presented here, a column is considered to behave as a threshold gate, that is, if a sufficient number of excitatory neurons fire, the column is said to be active and the respective feature present. If there are not enough firing neurons, the column is said to be non-activated and so is the feature it represents.
The neural preferences interpretation of a model with cortical columns acting as threshold gates is analogous to the case of single neurons and synchrony code. Let us consider a model of synchronously firing cell assemblies, with Δt being a time interval in which all spikes would be considered as synchronous. A sequence of synchronously firing assemblies will be defined in a sequence of intervals $\Delta t_1, \Delta t_2, \Delta t_3, \ldots$, where the s^{th} interval is defined as $\Delta t_s = \{\, t \mid t'_s < t < t''_s \,\}$, t'_s and t''_s are the beginning and the end of the interval, and $|\Delta t_s| = t''_s - t'_s$ is the length of the interval. In some implementations of spiking neurons, the sequence of intervals might represent a continuous time set, i.e. $t''_s = t'_{s+1}$, while in others there might be an explicit time shift between the separate intervals of synchronous firing, i.e. $t''_s < t'_{s+1}$. For each interval we can define $\bar{t}_s$ as the mean time of the spikes in Δt_s. Examining the spikes from time $|\Delta t_s|$ before t_s and $|\Delta t_s|$ after t_s, that is in interval $2|\Delta t_s|$ around t_s, we can define a spike time preference of a neuron (threshold gate column) in the interval Δt_s as:

$$a^i_s = \begin{cases} 1 - \frac{|t^i_s - \bar{t}_s|}{\Delta t_s} & \text{if neuron (column) } i \text{ has fired in the time window } 2\Delta t_s \\ 0 & \text{if neuron (column) } i \text{ has not fired in the time window } 2\Delta t_s \end{cases}$$

Here, t^i_s denotes the firing time of neuron (column) i. Then the vector $a_s = (a^1_s, a^2_s, \ldots, a^N_s)$ is the *c-preference vector of cell assemblies of single neurons or threshold gate columns* in the time interval Δt_s. According to the above definition of a_s, a higher density in the synchronous firing in the assembly will lead to values in the preference vector close to 1. Alternatively, lower density of the spikes inside the time window will lead to values close to 0.5. Finally, firing times outside the time window will lead to values close to 0 and therefore rejection of the represented features.
A *neural preference class of cell assemblies of single neurons or threshold gate columns* can be interpreted as a set of all preferences that represent the cell assembly for the same information with equal strength. This interpretation of the classes allows us to abstract from the particular distribution of the synchronous spikes in the time window usually considered as noise in biological systems.

4 Case Study: Clustering Sequences in a Pulsed Self-Organizing Map

We are currently working on a pulsed neural network approaches for semantic understanding based on feature binding and slot filling. As part of this work, we are developing and experimenting with a model of pulsed neural network for processing of sequential input data. The particular task described here is clustering of the input sequences in a self-organizing map.

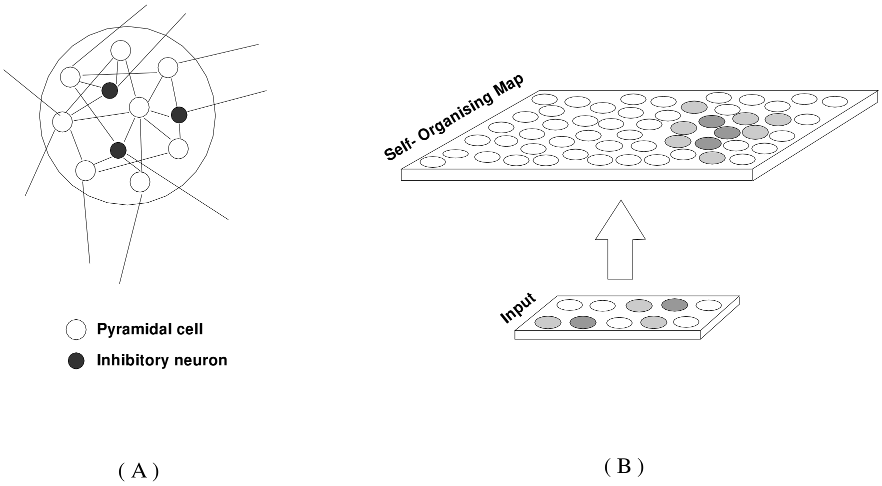

Figure 1: Example of a general pulsed neural network model of sequential input clustering, based on Hebbian assemblies of cortical columns. (A) Model of a cortical column used in the network. There is dense connectivity between the neurons within the column: inhibitory links from the inhibitory to the pyramidal cell and excitatory links between the pyramidal cells. (B) The two-layered model of the network. Each circle represents a single column from A. There is sparse connectivity between the neurons within a layer. However, on a single column level, the layer is fully connected with short range excitatory and long range inhibitory connections. Furthermore, there are feed-forward connections from the input layer to the map.

The network consists of two layers of integrate-and-fire spiking neurons and uses a model of a cortical column as a functional unit (Figure 1.). In the experiments described here, however, we used a single neuron to simulate the behavior of a column in the network. A neuron can send and receive excitatory as well as inhibitory signals.
The input of the network is encoded in a time-to-first spike code (Figure 2.). There is one main difference of our coding scheme in comparison with the standard time-to-first spike code, where the delay of the spike is set with respect to a global signal (usually presentation of external stimulus). We delay the spike of an input neuron with reference to its previous spike. With a single repeating input pattern, such a code scheme has the properties of frequency code. With a dynamic pattern (i.e. sequences), however, the code works on a level of precise timing of the spike and demonstrates properties that are valuable for the task of clustering dynamic patterns.
After the input sequence is processed, a cluster of neurons in the second layer enters in a locked synchrony mode. When some of the input neurons have been strongly stimulated from the beginning of the input sequence, the neurons could be locked in synchronous firing before the whole input has been processed. The

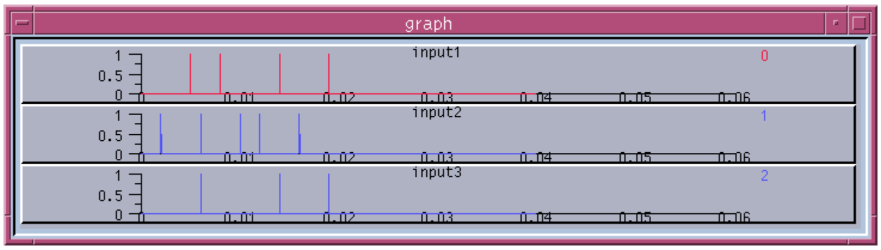

Figure 2: An example of three dimensional input sequence represented in the time-to-first spike code. The input is: (0.005, 0.002, 0.006), (0.003, 0.004, 0.008), (0.006, 0.004, 0.005), where each value represents a delay in the spike (sec).

output cluster is allocated around the neurons that have fired first. In such a model, the precise timing of the spike determines which neurons and which cluster of the map are "winners". Furthermore, the synchronous firing of that cluster interpreted as a Hebbian assembly defines which features of the output are exactly activated (Figure 3.).

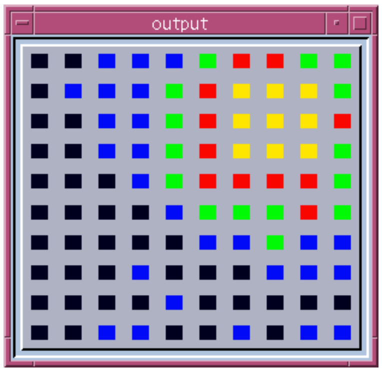

Figure 3: An example of the output after processing the above sequence (without entering locked synchrony mode).

The model applies a Hebbian learning algorithm based on the temporal correlation between the post- and pre-synaptic spikes. If the pre-synaptic spike has arrived within a certain time window before the post-synaptic neuron fires, the synaptic efficacy is increased. If the pre-synaptic spike arrives within a certain time after the neuron has fired, the synaptic efficacy of that link is decreased.
At a higher level of abstraction, such a model can also be viewed as a preference Moore machine (I, O, S, f_p). We can define the input set I to contain all simple preferences representing the network input set using time-to-first spike code. The output set O will contain the interpretation of the working memory in a synchrony code as cell assemblies. The state set S of the machine will contain complex preferences that are an interpretation of the output layer as cell assemblies. Such a preference Moore machine will perform a mapping from the input preferences which can be symbolically interpreted as language phrases and the current state as a complex preference from an output set of clusters.

5 Discussion and Conclusion

In this paper we have explored the use of preference Moore machines at symbolic and connectionist levels but, in particular, we have made some new contributions based on the neuroscience level. We argue that in the long run it will be necessary to understand more of the underlying neuronal processing and that symbolic, connectionist and neuroscience levels are useful levels of abstraction. By considering the neuroscience level, important new insights may be gained for higher symbolic connectionist levels.
Architectural abstractions at different levels are important in order to link higher level cognitive functions like language processing with the neuroscience level. The complexity of cognitive and neurobiological processes makes it seem plausible that several representational levels may be advantageous [Gutknecht, 1992, Sun, 1996]. Furthermore, although the cortex is relatively flatly structured compared to its size [Hubel and Wiesel, 1979], it is structured and far from random. It is partially predetermined at birth but also develops much further in particular in the first years [Bloom, 1993]. We would like to conclude that abstraction levels at symbolic, connectionist and neuroscience levels may be advantageous and that the preference approach is one promising way to link these levels for higher cognitive processing.

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