Overlapping Cell Assemblies from Correlators

Christian R. Huyck

Middlesex University, UK

1 Introduction and Background

The Cell Assembly (CA) [2] is a central concept in computational neuropsychology and cognitive science in general. The basic idea is that what we consider concepts are stored in the brain by reverberating neural circuits called CAs. Neurons that are connected by synapses with large strengths are the basis of CAs, and the CA is activated by some of its neurons being fired. These neurons then cause other neurons in the CA to fire leading to a cascade that ignites the CA enabling a reverberating circuit that can remain active longer than a single neuron could remain active.

Two cornerstones of CA theory are that Hebbian learning is the major type of learning in the brain, and neurons participate in multiple CAs [8]. Hebb's simple rule leaves a wide range of possible interpretations. There is biological evidence that Hebbian learning occurs in the brain [7], but the current state of neurophysiology does not provide the computational basis of this rule. Also, neurons participate in multiple CAs, so more CAs can exist and there is a wider range of interrelations between CAs. These interrelations are needed to form associative memories, cognitive maps, and more sophisticated structures.

This paper develops a principled Hebbian learning rule based on the notion of correlation, and then extends this correlational rule to allow CAs to form on a wide range of patterns. The extension, the compensatory rule, is then applied in a simulation where neurons participate in multiple overlapping CAs.

2 Hebbian Learning Makes Synapses Correlators

The Hebbian learning rule states that if node A is connected to node B, and both are activated, then the strength of the connecting synapse is increased. The logical extension of the Hebbian learning rule is that synaptic weights correlate how often the postsynaptic neuron fires when the presynaptic neuron fires. We have developed a learning rule that enables the synapse to tend towards a linear correlation value; the synaptic weight has a linear relation to how often the postsynaptic neuron fires when the presynaptic neuron fires. The formal proof of the learning rule can be found in [5] along with a longer description of the affect of different neural properties on synaptic weights. The rule takes advantage of the current synaptic weight as an approximation of the correlation to force the weight towards the real correlation value.

Hebbian learning makes synapses mere correlators, but biological neurons show that synapses are more. Neurons spread activation based on synaptic weights; this tends to increase the weights and via reverberation to markedly increase them. Neurons also fatigue which tends to reduce synaptic weights. Fatigue stops CAs; since active CAs are short-term memory items, fatigue automatically removes items from short-term memory.

Synapses spread activation from the firing presynaptic neuron to the postsynaptic neuron. This spread allows neural firing without external environmental stimulus and enables a reverberating circuit. A CA can be ignited either by directly stimulating neurons (see section 3) or by having neurons elsewhere in the network send activation to neurons in the CA. If there is enough activation, the CA will ignite via intra-CA stimulation making many of the neurons in the CA active. This percentage is gradually reduced due to fatigue, until the recurrent activity is no longer supported and the CA becomes inactive. The benefits of spreading activation include completion effects, maintaining a concept in working memory and passing information to other CAs. Completion effects enable a full CA to be activated even though only part of it is present in the environment. Finally, some neurons are inhibitory; this makes it easier to have CAs that compete but tends to decrease the excitatory weights.

The primary function of CAs is categorisation. A stimulus pattern is presented, activation spreads from these externally stimulated neurons to other neurons, and if there is enough activation the CA is ignited, categorising the stimulus as an instance of that CA. A CA is formed by Hebbian learning increasing the intra-CA synaptic strengths. This enables the CA to be a reverberating circuit, but this has now changed the connections from correlation measures to the primitives in a pattern attracting system. The stronger the connection, the more likely the neurons are to be in the same CA.

3 CAs with Neurons Participating in Multiple CAs

A fundamental tenet of CA theory is that neurons can participate in more than one CA [8] enabling more CAs and allowing more co-operation between

CAs. If neurons can participate in multiple CAs, it is possible to have more CAs than neurons [10]. CAs can communicate by neurons from one CA sending activation through their synapses to neurons in another CA, but when neurons are shared even more long and short-term information is communicated.

There have been many simulations of CAs that have created non-overlapping or orthogonal CAs e.g. [3,6], but it is more difficult to have neurons included in multiple CAs. With overlapping CAs one CA ignites and the neurons that are included in both CAs will ignite the other CA.

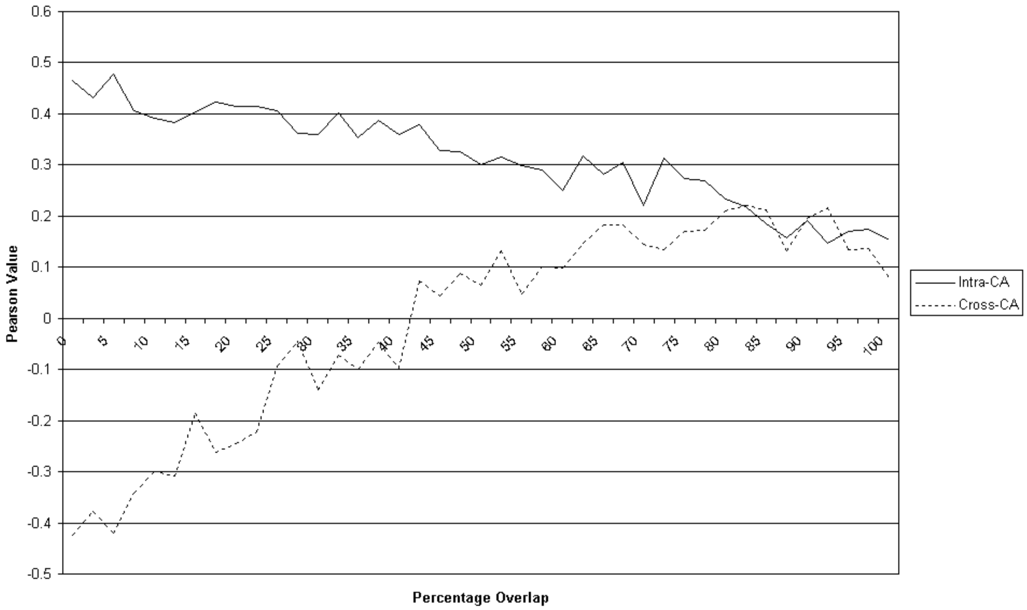
The compensatory learning rule solves this problem, and solves the problem of learning CAs for sparse patterns. The compensatory learning rule is a variant of the Hebbian learning rule. It is still a localist rule based only on properties of the pre and postsynaptic neurons, but it also considers the total strength of all the synapses leaving the neuron. If the overall strength is low, the new strength is increased a large amount. It is a post-hebbian learning rule [9].

Correlation learning raises synaptic weights only to a certain level. Spread of activation and reverberation can cause these levels to rise to near maximal values. However, low correlations may not provide sufficient activation to enable a reverberating circuit to form and this is the problem of sparse patterns. When neurons participate in only one CA, compensatory learning increases weights above correlational values for sparse patterns enabling CAs for a wider range of patterns.

When neurons participate in multiple CAs, their total synaptic weight based on correlation is higher. The compensatory rule reduces the weights making CAs compete for synaptic strength. Unfortunately, there has been little simulation of CAs when neurons participate in multiple CAs. Wickelgren [10] simulates this but uses biologically implausible neurons. Using the CANT model [5], we have simulated overlapping CAs with biologically plausible neurons.

Simulated networks learned overlapping CAs. The network consists of a 20x20 neural grid connected in a distance-biased toroidal topology. 20% of the neurons are inhibitory and all learning is done by the compensatory learning rule. Each net learned two types of patterns with each training cycle externally activating 20 neurons randomly selected from the pattern. Training presented alternating types of patterns to the net with no spread of activation for 3000 cycles. Simulations were run with between 0 and 100% overlap. In the orthogonal case (0% overlap), the patterns were either the top 10 rows or the bottom 10 rows, and with 100% overlap there is only one pattern.

The test presented one pattern for 10 cycles, then compared the state to a different pattern after 10 cycles. The measurement is Pearson's product moment correlation coefficient, testing whether a given neuron fires. Pearson's correlation is used because it ignores the inactive neurons, and in all cases,



Pearson Measurements: Figure 1.

most of the neurons are inactive. Figure 1 shows a series of comparisons of trained nets, averaged over 10 simulations.

The Intra-CA line is a comparison between different runs with instances of the same pattern, and shows that at least one CA is formed. The Intra-CA Pearson value stays positive but descends roughly linearly as overlap increases. This descent is due to a smaller percentage of neurons in the CA becoming active. As overlap increases, the size of the CA grows; the same number of neurons activate after ignition, but it is more likely that they will be different neurons on different runs.

The dotted Cross-CA line is a comparison between runs of the top and bottom pattern. In the orthogonal case the correlations are negative showing two independent CAs, but as the overlap grows, the network starts to develop one CA instead of two. It is sensing that both types of patterns are just variants of the same pattern. In this experiment that happens around 40% overlap.

4 Discussion and Conclusion

CAs may be the neural basis of human concepts and thus are crucial to our understanding of human intelligence. Studying CAs from simulated neurons enables us to gain an understanding of how they are learned and how they behave. CAs are pseudo-stable states similar to those in Hopfield nets [4]. We are trying to understand how these pseudo-stable states are reliably formed.

The particular Hebbian learning rule that is used is crucial to the development of these pseudo-states. This paper began by basing the learning rule on a linear correlator, then added a compensatory modifier that allowed multiple overlapping stable states. The simulations show how a net of biologically plausible neurons learns overlapping CAs. At some point the patterns merge into one CA with the extra variance being attributed to noise. This is an early step in studying overlapping CAs; a more complex system would have many overlapping CAs and CAs would compete to recruit neurons.

CAs can also communicate with each other to from more complex structures such as sequences and semantic nets [1]. Theoretically, they can even be bound together to form rules and short-term associations. Thus overlapping CAs can form the basis of sophisticated cognitive systems.

Acknowledgements: This work was supported by EPSRC grant GR/R13975/01.

References

[1] Fransen, E. *et al.* (1992) A Model of Cortical Assoc. Memory Based on Hebbian Cell Assemblies. *Connectionism in a Broad Perspective.* Niklasson & Boden ed.

[2] Hebb, D.O. (1949) The Organization of Behavior. J. Wiley & Sons, New York.

[3] Hetherington, P. A., and M. Shapiro. (1993) Simulating Hebb cell assemblies: the necessity for partitioned dendritic trees and a post-net-pre LTD rule. *Network: Computation in Neural Systems* 4:135-153

[4] Hopfield, J. (1982) Neural Nets and Physical Systems with Emergent Collective Computational Abilities. *Proceedings of the National Academy of Sciences* 79

[5] Huyck, Christian R. (2002) Cell Assemblies and Neural Network Theory: From Correlators to Cell Assemblies. Middlesex Uni. Tech. Report ISSN:1462-0871 CS-02-02

[6] Lansner, A. and E. Fransen. (1992) Modelling Hebbian cell assemblies comprised of cortical neurons. In *Network* 3:105-119

[7] Markram, H. , J. Lubke, M. Frotscher, and B. Sakmann. (1997) Regulation of Synaptic efficacy by Coincidence of Postsynaptic APS & EPSPs In *Science* 275

[8] Sakurai, Yoshio. 1998. The search for cell assemblies in the working brain. In *Behavioural Brain Research* 91 pp. 1-13.

[9] Shouval, H. & M. Perrone. (1995) Post-Hebbian Learning Rules In *The Handbook of Brain Theory & Neural Networks.* Arbib ed. MIT Press pp. 745-8

[10] Wickelgren, W. A. (1999) Webs, Cell Assemblies, and Chunking in Neural Nets. *Canadian Journal of Experimental Psychology* 53:1 pp. 118-131