Abstract - This paper suggests a statistical framework for describing the relations between
the physical and conceptual entities of a brain-like model. In particular, features and concept instances
are put into context. This may help with understanding or implementing a similar model. The paper
suggests that features are in fact the wiring. With this idea, the actual length of the connection is
important, because it is related to neuron synchronization. The paper then suggests that the
concepts are neuron-based and firing neurons are concept instances. Therefore, features become
the static framework of the interconnected neural system and concepts are combinations of these,
as determined by an external stimulus and the neural associations. Along with this statistical model,
it is possible to propose a simplified design for the neuron itself, but based on the idea that it can
vary its input and output signals. Some test results also help to support the theory.

Keywords: feature, concept, brain, neural model, network.

1 Introduction
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and conceptual entities of a brain-like model. In particular, features and concept instances
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the connection is important, because it is related to neuron synchronization. The paper then
suggests that the concepts are neuron-based and firing neurons are concept instances. The
concept can also vary based on neuron firing rates and strengths, for example. Therefore,
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1 Unfortunately, the author has used the term ‘synapse’ to mean the whole connection between neurons in
other papers and so the term synapse may be used to describe the whole connection or just the synaptic gap.
The context will make it clear.
associations. This view of the network would also relate to a grid, mesh, or tree structure, where features extend horizontally and the concepts vertically. Along with this statistical model, it is possible to propose a simplified design for the neuron itself, but based on the idea that it can vary its input and output signals. So these are the essential details of the paper that will be described further in the following sections.

The rest of this paper is organised as follows: section 2 describes some related work. Section 3 introduces the network idea of features and concepts, while section 4 describes a test result that would support the theory. Section 5 then describes a simplified neuron model that can make use of the theory and section 6 gives some conclusions to the work.

2 Related Work

The idea of simply defining the neuron connections as features has come directly from a new neural network model described in [4]. That model showed that features in a dataset can be uniquely recognised from individual columns and without any weighted processing or aggregation. The biological paper [17] looks at neural plasticity and argues that neurons have multiple input connectors to filter synaptic potentials and electrically isolate input signals from each other. It is also their purpose to add plasticity to the circuits of fixed neurons and connectors, where it might be difficult for a network to change after it has realised a large fixed structure. So if the structure cannot change, it may be better to allow flexible combinations of activations over it. The paper [6] used a different grid model to separate the data into discrete bands and it was found to have some relevance to a controversial paper [1] which suggested that long-term memory is not stored in the synapses, but in the neurons themselves. Synapse here means the neuron connections. The synapses can be destroyed and when they grow back, they may be different, but the long-term memory traits are the same. They state that: ‘Yet there’s no known mechanism by which a neuron could store a molecular ‘map’ of its own connections and their differing strengths’, where a pattern of different strengths is required. While is is generally thought that a neuron acts as a single unit, new research [15] suggests that a neuron can function as
an anisotropic threshold unit. The neuron would contain many independent excitable sites, each functioning as an independent threshold unit which sums up the incoming signals from a given limited spatial direction. But they indicate that the output is the same, travelling though the single Axon to the synapse connections. It would be interesting if the variation in input could provide a corresponding variation in output, even if it was only to activate different synapse groups. So, this paper will suggest that some type of signal strength (or molecule size?) inside of the neuron is able to direct the signal through different inter-neuron links, but as always, this has to be done statistically, without intelligence. This is written about again in section 5.

Two other papers measured neuron synchrony and activation [2][13]. The paper [13] built a detailed computational model of the brain and noted that synchronization and oscillation between the neurons is related to distance, or a small delay in firing sequences. Without a delay, there was no oscillation. However, it also noted other factors, including a radius of influence around a neuron, as in: ‘Connecting a neuron to all neighbors alike within a radius r makes the delay distribution very skewed and biased toward the largest delay values. Either the connection probability or the synaptic weight, therefore, needed to fall off with distance from the source neuron.’ It also considered the inhibitory signals to be more important in managing the timing, for reasons of controlling the excitation. They also found that only a few connections, say 5 for each neuron instead of 100, could activate a network to full strength, which does ask what the rest of the input would be doing. Resonance also occurs at full strength and they concluded that the oscillation frequency that the resonance would occur at is affected more by synaptic delays, over factors like signal strength or decay time constant. The paper [2] measured the effects of a single neuron and found that it would excite its immediate neighbourhood, but then switch off most of the area outside of that. It would, in fact, compete for the input, rather like a Self-Organising Map [12]. This would help to reduce noise and create a small cluster that would clearly define the input. This was not the whole story however and some neurons further away but also tuned to the input would still be excited, maybe like a small-world effect [16][3]. They could therefore carry the signal somewhere else, but the message here was a radial distance from a neuron and not very specific distances. But the work shows that a single neuron can have a significant
affect on the whole network and it suggests an almost opposite effect to this paper. Neurons that were tuned to respond to similar features competed and more strongly suppressed each other than neurons with a different tuning. This inverse relationship remained true regardless of the distance between neurons. Or is the inhibitory system again required to stop the excitatory one getting out of control and how fine-grained is the tuning?

Memory is also part of this paper’s model and is also required for the long-term memory findings in [1]. This suggests looking at the single cell animals that have memory, or their Memristor computer-designed counterparts [14]. This has been done in various papers, where in [3] they try to integrate Memristors with small-world networks and the associative memory Hopfield networks. They design synapses using this model.

3 Features and Concepts

With this design, features are the static structure of the network and concepts are instantiations of feature sets. Features and concepts represent fundamentally different things, even though they are integrated in the same structure. The features are static descriptors while the concepts are value based and dynamic. A feature is a single entity while a concept is an aggregation. Features are more physical while concepts are more resultant. This view of the structure would also relate to a grid, mesh, or tree structure, where features extend horizontally and the concepts vertically. The features cumulate horizontally into a concept and the concepts build on each other, to provide a search path.

Considering the network structure then, it may be the case that the inter-neuron distances are significant and can be compared to features. This makes good sense, because if equidistant neurons fire at the same time, then they are likely to represent the same thing and can be mapped to the synapse (wiring) itself. A small point may be the following: it was found to be mathematically the case that equal spacing between neurons is also the most economic setup, with regard to energy usage [10]. Therefore, if a set of neurons are firing together as a single concept, equal spacing between them would be best. Then as described
in [2], links to other firing features should be minimal, where they might similarly synchronize using equals distances in their own clusters, rather like the small-world effect [3]. With this setup, the synapse distance is static knowledge, while the neuron firing rate is more dynamic and can change with the situation. Putting one’s hand in the fire, for example, belongs to a different subset than warm water.

One question is why would a model want to use the inter-neuron distance as a feature. Apart from possible economic reasons, a computer model may find it attractive because it helps to compartmentalise the network. A program would ultimately want to add symbols to the neurons so that everything can be understood. As this is not possible, a defined distance can be used to assign a weak symbol to a set of connections, or connection plus neuron type, etc., thereby increasing the knowledge level by a small amount. While the statistics are automatic, the design may require a neuron to have some memory and the problem is if this is biologically realistic. As single cell organisms can be modelled as Memristors however [3][14], a neuron might be able to display memory properties. Section 5 describes this further.

3.1 Integrated Model

The paper [8] re-defines the 3-level architecture into a more human-like vernacular. The upper cognitive layer is not considered yet and so there is a mapping to the first two levels only. These are a bottom optimising layer and a middle aggregation layer. Considering the bottom optimising layer, while it is for optimising links in patterns, it is also described in terms of ‘Find’ or ‘What’ functionality. This has an obvious mapping to features, because any search process starts with a set of initial features. It is also horizontal in nature, because the search will try to find best combinations of the feature set before moving to the next stage. The middle layer is for aggregation of the links which also includes averaged decisions over them. As the neurons would receive a feature set as input, they can be considered to be aggregators. It may be interesting if different features can be represented by exactly the same synapse structure – same length and signal strength, but be distinct by the path they take through the network, for example. This would not be distinguishable if viewing it from the outside. Therefore, the input synapse lengths can help to regulate the neuron firing
rates, which determine what neurons on further paths may fire in-sync with the current set. But the actual connection setup between neurons can also determine different features with identical structure, thereby allowing the system to provide a much greater variety of information. If the information is aggregated, then we get a summary of it. This can relate to a ‘Compare’ or ‘Why’ function that is a level above activation. The aggregating structure also indicates rules, based on consistent signal activity more than signal path and so it becomes more dependent on neuron values, which represent concept instances more than integrated feature sets. Aggregation through the neurons is therefore more vertical in nature.

4 Feature – Value Test
Some of the earlier research has realised a number of classifiers that can be used to cluster data based slightly different criteria. For example, the cohesion equation of [8] was compared to the Chi-Square measure [11] in the paper, but as it deals more with subsets of data rows and not columns, it probably measures something different. This could explain why the Chi-Square measure did not compare well in those tests. In a new set of tests, a computer program written in Java, presented parts of an ontology to clustering algorithms, to see how well they would re-construct the ontology. A level of noise was set, but if this is very low, then the algorithms would be expected to re-construct the ontology exactly. Two different types of clustering mechanism were used, which was the linking mechanism [9] and the Frequency Grid [5]. The Frequency Grid is more feature-based and considers similarity along data columns, while the dynamic linking mechanism is more value-based and considers local link instances only. The algorithms learned the small cluster parts of the ontology as determined by the random presentations, but to learn every link would require a lot more iterations. The two cluster sets were slightly different however and if they were then combined, it gave a much better view of the larger whole cluster sets that they were learned from. Because there was overlap in the two cluster sets, putting them together would actually give a view of the whole ontology from two sets of parts.

As an example, an ontology was written with 4 different types, each with 10 instances, giving a total of 40 nodes. There were also 6 inter-pattern links to count as noise. A random
number of up to 5 nodes from a pattern would be presented each time, where 50% of the time an inter-pattern link would be selected if it existed, and the clustering algorithms would learn the correct associations. After 500 iterations or presentations, the linking mechanism and the frequency grid had learned the following information about the underlying onology: The linking mechanism created 10 clusters and the frequency grid created 16 clusters, with an inherent problem that some clusters have only 1 entry. Because of the overlap, if the two cluster sets were combined, the original 4 cluster sets would be realised. So there is a question about whether these two views can give a better picture of the whole, or if they can re-construct the whole in a quicker time.

5 Simplified Neuron Model

This section proposes a very simplified model for the neuron and the neural system. It is clear from a lot of research that the connection length between neurons may not be the principal consideration and so it is proposed here as only one of several indicators. Others include the neuron type and simply proximity to the firing node. A path to nodes can represent a search path through specific neuron sets, joined together by the connection features that make up the path. What is required is a flexible way to select the path. Some research has suggested that the neuron output is more vector-like [1] and other research has described how a neuron can output more than one scalar value. This can correlate simply to a stronger input signal resulting in a stronger output signal. One idea for a simplified neuron would therefore be to replace the single output value by a variable structure. The continuous input can even be split-up into discrete bands [6] that may be easier to manage. So what is required is a mechanism for the neuron to recognise a signal difference internally and use that to trigger a different output signal. An action potential might be an option and that was used as part of a network-wide oscillating technique in [7]. The paper [15] however argues for this sort of thing inside of the neuron or input dendrites web. In [7] a mechanism was presented that allowed neurons to oscillate between some upper limit representing a larger ensemble and a smaller local value representing the neuron itself. The mechanism also suggested to turn a neuron switch on or off, to help to activate the network parts. The switch would be managed by the parent ensemble or the
neuron itself. The threshold unit of [15] might be recognised as part of this process, if the neuron fires at at least two different rates, thereby creating an action potential between two different states. If the neuron can remember the last state it was in, then it can compare that with its current state. Or if it in fact averages over a series of signals, then the value can vary over time.

If considering the statistics of this process then, a weak association would send a signal back into the whole ensemble, as a general reinforcement signal. If the neuron is more active, then the signal strength increases (and the action potential would decrease) and it becomes a significant feature. In that case the output signal is made stronger and it also becomes more specific, linking with fewer nodes in the network. The weak association would therefore send out any signal when possible, which would include all of the search misses that go through the neuron. The stronger signal must be more specific and when that happens, it would be ideal if the output was also more specific. If it was up to statistics alone, then that would probably be the case. If considering a neuron as part of a larger network, there may be other statistical reasons why it is able to remember its connections as part of a memory. Even if the neuron gets damaged and needs to repair, that would be influenced by the surrounding patterns and they maintain the earlier connections and activations. When the neuron therefore re-constructs itself, it takes on the same characteristics as before.

5.1 Neuron Synchronization

It has been demonstrated [2] that neurons can take part in a winner-takes-all scenario, where the winning neuron switches-off its neighbours. In this way, it can form a small and distinct cluster to represent its own feature. While the immediate neighbourhood is switched off, neurons further away but also tuned to the input can be activated, thus sending the signal to a different region, probably to represent a different complementary feature. So that is good for the model in [10] but suggests that equal distance between neurons is not as important as a radial distance. Neuron synchronization however requires that the neurons fire at the same time and so a time lag is significant. The neurons in a region may therefore compete for the signal when they are close to each other, but if the
neurons are not in-sync, then does the inhibitor have the same effect? If there is a small delay in the firing sequences, maybe due to longer inter-neuron connections, then the inhibitory signal might not switch off a neuron that was currently inactive, or was already in a depolarised state. This would allow those neurons, representing a different related feature, to subsequently fire more easily.

6 Conclusions
This paper gives one possible view of a brain-like structure and while this model is not completely surprising, it may help to focus on the different types of component more clearly. To use the model however, it would have to be accepted that the signal in the wiring is equally important when it comes to something like consciousness. The framework has been reduced to the bare components that interact through statistics only. If the network wiring stores the features, then an input stimulus activating different sets of neurons over this can be flexible enough to create different types of concept and the network itself does not have to change. It would be desirable that a neuron's output is correlated more closely with its input. It would therefore connect with other neurons based on a value range. When the input is more specific then so is the output, which would also be statistically correct. Considering the operation of each individual neuron, it would be interesting if the network behaviour was repeated in the neuron itself. This would help to model some aspects of memory and a slightly more intelligent connection strategy. The environment would also directly influence the neuron behaviour, which is stigmergy at work.

Tests showed that two different clustering mechanisms, one representing the environment features and one representing the environment instances, produced a much better cluster description when combined than separately. Each produced small sets of clusters that overlapped and if the overlap was also considered, then the cumulated cluster was a much better representation of the whole entity. An idea of the ‘whole’ is another important concept in brain theory and even something like Deep Learning has problems with it.
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