Self-Organising Networks for Classification Learning from Normal and Aphasic Speech

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Abstract

An understanding of language processing in humans is critical if realistic computerised systems are to be produced to perform various language operations. The examination of aphasia in individuals has provided a large amount of information on the organisation of language processing, with particular reference to the regions in the brain where processing occurs and the ability to regain language functionality despite damage to the brain. Given the importance played by aphasic studies an approach that can distinguish between aphasic forms was devised by using a Kohonen self-organising network to classify sentences from the CAP (Comparative Aphasia Project) Corpus. We demonstrate that the different distributions of words in aphasics types may lead to grammatical systems which inhabit different areas in self-organising maps.

Introduction

The examination of neural language processing is of importance as it offers the opportunity for producing realistic computerised language systems and a comprehension of the underlying biological mechanisms and constraints involved. One technique that has proved useful for identifying the organisational arrangement of language processing is the examination of aphasia. Aphasia is the inability to perform one or more cognitive language functions due to damage to the brain. The typical causes of aphasia are brain tumours, strokes, head injuries and infections. Although this is a rough simplification, the two most common types of aphasia are Broca's and Wernicke's aphasia.

Broca's Aphasia: Subjects with damage to the Broca's area of the cerebral cortex have problems creating spoken responses. These responses are often grammatically incorrect, effortful, laboured, come in bursts and have a restricted vocabulary. Furthermore, verbs are often missed out or replaced by the nominal form in spontaneous speech. However, many individuals with this condition can perform language processing functions such as language comprehension, dealing with non-reversible sentences, object and verb recognition and the identification of semantic and verb errors. Table 1 provides examples of typical spontaneous speech from Broca's aphasics [Wermter, Panchev and Houlsby (1999), Marshall, Pring and Chait (1998) and Brendt and Caramazza (1999)].

Wernicke's Aphasia: Although individuals with Wernicke's aphasia have problems understanding language and producing sentences that are meaningful, they can produce fluent phrases that have a reasonable syntactic, grammatical and symbolic structure [Chen and Bates (1998) and Wermter, Panchev and Houlsby (1999)]. Table 2 provides examples of spontaneous speech from Wernicke's aphasics.

An approach previously used to distinguish aphasic forms is recurrent neural networks [Wermter, Panchev and Houlsby (1999)]. Such networks can represent long term memory and context using recurrent connections and extracting the appropriate context from inputs. In the simple recurrent network outlined by Elman (1990) the context layer stores the activations of the hidden layer units for one time step and passes them back to the hidden layer units on the next step. Typically there is a one-to-one relationship between the number of units in the context layer and in the hidden layer [Spitzer (1999)]. This offers the opportunity to recycle information from multiple time steps and to identify temporal relationships. As the hidden layer receives inputs from both the input and the context layer, patterns should have an impact across time and context be learned.

However, there are certain drawbacks with recurrent neural networks which led us to consider an alternative approach. Recurrent neural networks are a *supervised* learning approach that do not perform in a manner that is close to neural networks in the human brain. Therefore in this paper we used *unsupervised* self-organising networks that can identify categories, features and regularities using unsupervised learning in a manner closer to the cerebral cortex. In this paper we analyse spoken language from Broca's aphasics, Wernicke's aphasics and normal patients. We demonstrate that the different distributions of words in aphasics types may lead to grammatical systems which inhabit different areas in self-organising maps.

Location of Aphasia and Language Function

The examination of aphasics provides some indication of how language processing is organised and the form that language recovery takes. A language processing model that has been established from studying the location of damage in the cerebral cortex of aphasics is that the human brain performs diverse language processing opera-

Table 1: Typical spontaneous speech from Broca's aphasics.

Normal phrase	Broca's aphasic response
A boy is giving the ball to the man	A boy is ... the ball
A monkey is eating a banana	Monkey ... banana
Chrysanthemum	Chrysa...mum...mum
Cat cries	Cat tears

Table 2: Typical spontaneous speech from Wernicke's aphasics.

Typical Wernicke's aphasic responses
They are running a swimming water and snow
The boy is running he is talking to the it is a cat
It is a cat and he is talking the flower

tions. According to Taylor (1999) and Dodel, Hermann and Geisel (1999) the cortex is made up of various somewhat overlapping regions which are responsible for cognitive language sub-operations. In order to produce the final language functions there is a need to coordinate and combine the outcomes of the appropriate regions. According to Reilly (2001) the brain performs as a group of collaborating specialists, none of which can deal with a difficulty alone, but only do so when each cooperates. In the brain it is possible to deal with a complex difficulty by splitting the task into smaller elements and coordinating these elements. The uniqueness of the human brain does not come from the number of neurons but the structural complexity. It has been identified that the module approach can offer re-usability by having a region of the brain doing the same processing activity as part of many different cognitive functions [Reilly (2001)].

In terms of the actual functions that are associated with diverse regions of the cerebral cortex a few examples will now be outlined. When Binder, Frost, Hammeke, Cox, Rao and Prieto (1997) required individuals to state whether an animal was native of America and used by humans, different principal regions of the cerebral cortex were established as responsible for the language processing involved: (i) an area incorporating the superior temporal sulcus, middle temporal gyrus and parts of the inferior temporal gyrus; (ii) sections of the inferior and superior frontal gyri, the middle frontal gyrus and the anterior cingulate; (iii) angular gyrus; and (iv) a region containing the posterior cingulate and gyrus zones.

Silent word generation starting with a certain letter takes place in Broca's and Wernicke's areas and sections of the left frontal, temporal and parietal lobes [Papke, Hellmann, Renger, Morgenroth, Knetcht, Schuierer and Petersen (1999)] and the resolution of whether two words belong to the same semantic group involves increased activity in the superior frontal gyrus and frontal gyrus [Shaywitz, Shaywitz, Pugh, Constable, Skudlarski, Fulbright, Bronen, Fletcher, Shankweiler, Katz, Gore (1995)]. Finally, the process of generating verbs out loud was found by Xiong, Rao, Gae, Woldroff, Fox (1998) and Raichle, Fiez, Videen, Macleod, Pardo, Fox, Petersen (1994) to be associated with areas of the left posterior temporal cortex, right anterior cingulate, inferior frontal gyrus, Broca's area, left superior temporal gyrus, cingulate gyrus, inferior temporal gyrus and the occipital gyri.

The examination of aphasia has assisted in creating models of the form that the recovery of language processing takes in the brain. Examinations of the brain following death have identified injuries to parts of the cerebral cortex in normally functioning individuals which should have produced aphasia. This led to the view from Karbe, Thiel, Weber-Luxenburger, Herholz and Heiss (1998), Basso, Gardelli, Grassi and Mariotti (1989) and Capp, Perani, Grassi, Bressi, Alberoni, Franceschi, Bettinardi, Todde, and Frazio (1997) that language functions are recovered through regeneration of the damaged tissue or the redistribution of functionality to other regions of the brain that are operationally linked but not required in healthy individuals.

There is mixed research evidence for the time it normally takes for repair of injured tissue. However, researchers have found than redistribution of functionality to new regions of the brain can take longer and repair of the left superior temporal gyrus occurs over numerous months following the injury [Mimura, Kato, Kato, Santo, Kojima, Naeser and Kashima (1998) and Weiller, Isensee, Rijntjes, Huber, Müller, Bier, Dutschka, Woods, Noth and Diener (1995)]. As early as in the 19th Century Gower determined that individuals who lost speech due to damage to the left hemisphere were able to recover it through interaction with the right hemisphere. The region of the right hemisphere analogous to Broca's area and the right perisylvian have taken over the functions associated with the Broca's and Wernicke's areas respectively when they are injured. According to Reggia, Shkuro and Shevtsova (2000) the reorganisation of the brain regions responsible for language explains the remarkable capacity to recover from injury and robust, fault-tolerant processing. So in summary several brain regions may be involved with aphasia, even though at a highest level often a distinction of Broca's and Wernicke's aphasia has been made in the past.

Classification of Aphasia using Self-Organising Networks

As aphasia studies provide a significant amount of relevant information regarding the organisation of brain processing, there is a motivation to develop an approach to classify interviewed subjects to distinguish the aphasia form they have.

Method Overview

The language transcripts used for the training and test data sets for a self-organising network were obtained from the CAP Corpus [Bates, Fredrici and Wulfeck (1987a and 1987b)]. The CAP Corpus is made up of transcripts of English-speaking subjects that are divided into three groups: Broca's aphasia, Wernicke's aphasia and a control group of healthy people. The language transcripts were produced using a variation of the "given-new" picture description task of MacWhinney and Bates. In this task subjects were shown nine sets of three pictures and were asked to describe them (see Table 3). The transcripts contained the subject's response and the morphemic coding. We used the coding from a previous study by Wermter, Panchev and Houlsby (1999). This maps the morphemic coding of the corpus patterns using the following syntactic descriptors: DET (Determiner), N (Noun), N-PL (Plural), PRO (Pronoun), PREP (Preposition), ADJ (Adjective), CONJ (Conjunction), V (Verb), V-PROG (Progressive), AUX (Auxiliary Verb), ADV (Adverb), ADJ-N (Numeric).

Unsupervised Learning

The self-organising network that was used consists of an input and an output layer, with every input neuron linked to all the neurons in the output layer [Spitzer (1999), Hecht-Nielsen (1990), Kohonen (1997) and Anderson (1999)]. A self-organising network can be used by itself or as a layer of another neural network. Input data is presented one sample at a time and the nodes compete against each other. The Kohonen layer creates a topographical representation of the critical characteristics of the input by creating a pattern of active and inactive units (see Figure 1). The activation of the units are calculated by multiplying the input from each input unit by its related synaptic weight and summing all the inputs for a specific unit.

Learning in self-organising networks is performed by updating the links between the input layer and the output layer via a form of Hebbian learning. Self-organising networks attempt to depict the input data with a set of models, with similar words and concepts producing models that activate the units in the output layer that are close together.

Fitting of model sectors is performed by a sequential regression procedure, where $t = 1, 2, \ldots$ is the step index: For every sample $x(t)$, the winner index c is established by the condition

$$i, \;\; x(t) - m_c(t) \qquad x(t) - m_i(t)$$

Once this has occurred, every model vector m_i or a subgroup of them that belong to units centred around unit $c = c(x)$ are altered as

$$m_i(t \quad 1) = m_i(t) \quad h_{c(x),i}(x(t) - m_i(t))$$

The 'neighbourhood function' $h_{c(x),i}$ defines those units that are to be updated.

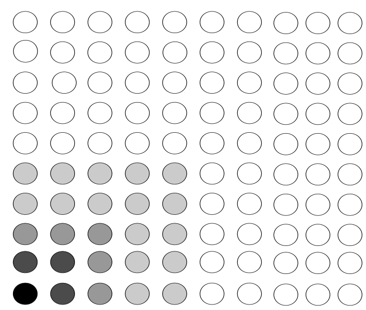

Figure 1: A representation of the activity maps of a self-organising network - The darker the neuron the greater the activation.

The self-organising network architecture considered to classify aphasic types contained 100 units (10 x 10) in the output layer. Using a different training/test set pair a self-organising network was trained and tested using the following approach. A network was trained over 1000 epochs using 80 phrases for each of the three aphasic types (Wernicke's aphasics, Broca's aphasics and a healthy control group) that were produced from the CAP Corpus. So in total there were 240 phrases. The location of each of these training phrases on the self-organising maps was identified based on the units that had the highest activation. The trained network was then tested by identifying where on the map 80 unseen phrases per aphasic type are positioned and the degree of symmetry between the training and test samples. The objective was to test if the phrases for Broca's and non-Broca's aphasics are located in different regions of the map and whether the network is able to generalise by placing the test phrases for the two groups in the same regions as the training ones. If the same unit has the highest activation level for phrases from both groups the unit is allocated to the aphasic type that has the most phrases associated with it. The grouping of Wernicke's aphasics with the healthy control group is motivated by the observation that Wernicke's aphasics often use correct syntax like the healthy control group while Broca's aphasics do not.

To remove any bias in classification and clustering the test/training phrases are based on the first six words of

Table 3: Picture series.

Syntactic Description	Sentences
DET N AUX V-PROG	A bear/mouse/bunny is crying.
DET N AUX V-PROG	A boy is running/swimming/skiing.
DET N AUX V-PROG DET N	A monkey/squirrel/bunny is eating a banana.
DET N AUX V-PROG DET N	A boy is kissing/hugging/kicking a dog.
DET N AUX V-PROG DET N	A girl is eating an apple/cookie/ice-cream.
DET N V PREP DET N	A dog is in/on/under a car.
DET N V PREP DET N	A cat is on a table/bed/chair.
DET N AUX V-PROG DET N PREP DET N	A lady is giving a present/truck/mouse to a girl.
DET N AUX V-PROG DET N PREP DET N	A cat is giving a flower to a boy/bunny/dog.

Table 4: Three word phrases for the aphasic types and their numeric representation.

Aphasic Type	Phrases	Syntactic Description	Numeric Represention
Broca's Aphasic	Banana three eat	NOUN ADJ-N VERB	1100 1010 0010
Broca's Aphasic	Boy is sport	NOUN AUX NOUN	1100 0100 1100
Wernicke's Aphasic	Little small here	ADJ ADJ PREP	0101 0101 1001
Wernicke's Aphasic	Squirrel with banana	NOUN PREP NOUN	1100 1001 1100
Healthy Control	The banana eating	DET NOUN V-PROG	0110 1100 1000
Healthy Control	A young boy	DET ADJ NOUN	0110 0101 1100

the sentences. A sliding window of three words that moves along one word at a time is used to create the final training/test three word phrases. Hence, if a transcript includes a sentence *"The monkey is sitting down eating a small yellow banana."* the first six words obtained are *"the monkey is sitting down eating"* and two of the training/test phrases are *"the monkey is"* and *"monkey is sitting"*. Since every word of these phrases is represented by a four digit binary number, the input layer for the network architecture has twelve units. The binary representations for the word are Determiner (0110), Noun (1100), Plural (0011), Pronoun (0111), Preposition (1001), Adjective (0101), Conjunction (1011), Verb (0010), Progressive (1000), Auxiliary Verb (0100), Adverb (0001) and Numeric (1010). Table 4 shows typical reponses of the aphasic types and the numeric representations that were input for the self-organising networks.

Results

Figures 2 and 3 show that it is possible to identify clear regions of the self-organising networks that are associated with the Broca's aphasic test phrases for both the test and training data. For Broca's aphasics there are two clear regions of the map, which is an indication that two forms of the condition might exist. For the two maps the Wernicke's aphasic/healthy control group are distributed around the rest of the map. When considering the test and training sample locations it is clear that the areas of the map associated with the test Broca's aphasics are very similar to the training ones. In many cases the cells with the highest activiation are exactly the same for the training and test samples. Therefore, unsupervised self-organising networks are a suitable alternative to supervised approaches for classifying aphasic types.

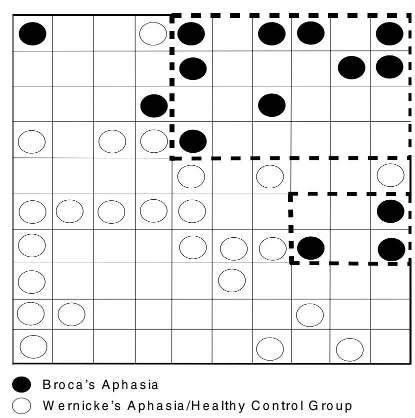

Figure 2: The regions on the self-organising map for a network based on 12 input and 100 output layer units associated with the second training set phrases for the aphasic types.

It is often the case when neural networks are trained to learn grammatical structures that two classes of examples are used; grammatically correct and incorrect phrases. The self-organising network architecture used in this paper is more general than these networks as it can identify three grammatical phrase structures, where the

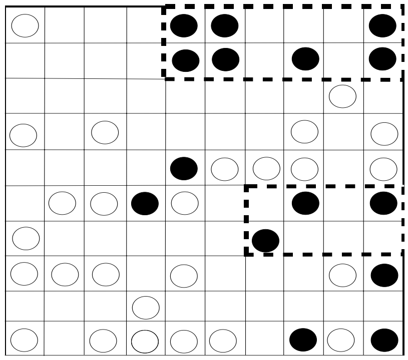

Figure 3: The regions on the self-organising map for a network based on 12 input and 100 output layer units associated with the second test set phrases for the aphasic types.

test phrases contain both typical and non-typical grammatical structures. Since phrases for the healthy control group/Wernicke's aphasics and Broca's aphasics are located at different regions on the self-organising maps it may be possible to develop a model of how the brain represents and processes grammatical structures of different individual types [Zurif, Swinny, Parther, Solomon, and Bushell (1993), Hartsuiker and Kolk (1998) and Marshall, Pring and Chiat (1998)].

The results in our experiments indicate that unsupervised networks are a suitable alternative to supervised approaches for classifying aphasic types. In terms of cognitive science the results show that while the spoken output of Broca's aphasics has a very distinct grammatical structure, healthy individuals and Wernicke's aphasics are much closer. This supports the view that language production may be based on a modular but interactive approach associated with particular regions of the brain and that correct grammatical construction is dependent on Broca's area.

By identifying two clear zones of the output maps associated with Broca's aphasics these could be associated with different degrees of injury and performance. If this is the case the different individuals in the two groups could provide the basis of a computational model of different levels of Broca's injury and hence of recovery. A final issue for consideration is why those classified as Broca's aphasic by the self-organising network failed to recover functionality by either tissue recovery or functional redistribution. A case examination of these individuals might provide information on the factors that are significant in functional recovery such as age, extent of injury and the type and level of medical intervention following injury.

The approach in this paper for classifying different aphasic types using a self-organising network was based on the difference between the grammatical constructs produced. This is an important step in our research with our overall aim being to incorporate other spoken language characteristics such as semantics and vocabulary level into the classification process by using a set of self-organising nets. The impact of that would be to produce a benchmark approach to classify many more aphasic types using a self-organisation approach and so provide cognitive scientists with a powerful diagnostic tool.

An additional advantage to cognitive scientists from the extented classifier is the removal of the subjective manner by which researchers include and exclude aphasics from pooled studies. For example, when considering if Broca's aphasics can deal with reversable sentences Brendt and Caramazza (1999) state that the percentage that cannot deal with these sentences is much less than those identified by Grodzinsky, Piñango, Zurif and Drai (1999) from the examination of the same pooled studies. Brendt and Caramazza (1999) add that the difference comes from Grodzinsky, Piñango, Zurif and Drai (1999) willingness to exclude Broca's aphasics. It is argued that they are not true Broca's aphasics. Finally, this system should offer an indication of the underlying organisational properties of language in the brain and so assist with the development of computational hybrid neural processing models [Wermter and Sun (2000) and Wermter and Meurer (1997)].

Conclusion

Studying individuals that have aphasia has provided a great deal of information connected with the nature of language processing and how the brain is able to recover language functionality following injury. By using self-organising network architectures it is possible to distinguish between a control group of healthy individuals/Wernicke's aphasics and Broca's aphasics using sentences from the CAP Corpus. One possible reason for the self-organising network's ability to separate the inputs into these two groups is their capacity to learn the grammatical structure produced by these aphasic types, which typically for Broca's aphasics are grammatically incorrect and for Wernicke's aphasics/healthy individuals are grammatically correct.

Acknowledgments

This research has been funded in part by EPSRC GR/M56555/01 awarded to Prof. Wermter.

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