Language disorders in the brain: Distinguishing aphasia forms with recurrent networks

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Abstract

This paper attempts to identify certain neurobiological constraints of natural language processing and examines the behavior of recurrent networks for the task of classifying aphasic subjects. The specific question posed here is: Can we train a neural network to distinguish between Broca aphasics, Wernicke aphasics and a control group of normal subjects on the basis of syntactic knowledge? This approach could aid diagnosis/classification of potential language disorders in the brain and it also addresses computational modeling of language acquisition.

Introduction

Within the field of artificial neural networks, the biological models from which they were originally inspired continue to offer a rich source of information for new developments. Conversely, computational models provide the power of simulations, to support the understanding of neurobiological processing systems (Hinton and Shallice 1989). The study of language acquisition is an especially important part of this framework, not just because of the importance of language-related neural network applications, but also because it provides a very good basis for studying the underlying biological mechanisms and constraints involved in the development of high-order cognitive functionality.

As part of this, studies on aphasia are directed at solving two major problems: the clinical treatment of aphasia patients and the computational modeling of language processing. In parallel with the psychological and linguistic aspects, computational simulations constitute a very important part of these studies - helping to understand the representational and functional language processes in the brain. There is a broad range of open questions that need an adequate answer before we reach any significant success in our computational models. These questions start from very precise biophysics or biochemistry problems, pass through many interdisciplinary ones within the Nature v Nurture debate (Elman *et al.* 1996), localist and distributed representational/functional paradigms, language localization and plasticity paradigms and finally many questions arise in the application and theoretical levels of linguistics, psychology and philosophy.

There are two major directions for studying the representational and functional processing of language in the brain. We can study the emergent language skills of humans, e.g. innate vs. learned, or we can study the effects of language impairments such as those due to brain injury, e.g. aphasia.

Discussing the first direction, some authors attempt to use new developments in neuroscience (and neuromodeling) to make sense of issues as development and innateness, from a connectionist viewpoint (Elman *et al.* 1996). They argue that there is a lot more information inherent in our environments, and that we therefore require much less innate hardwiring at cortical level than was previously thought. In their own words, "Representational Nativism is rarely, if ever a tenable position", and "the last two decades of research on vertebrate brain development perspective force us to conclude that innate specification of synaptic connectivity at the cortical level is highly unlikely".

Discussing the second direction, the study of human language impairments also provides a source for our understanding of language. For quite a long time, the link between left-hemisphere injury and language impairments has been known and studied (Goodglass 1993). Most of these studies supported the notion of strong precoding of language processing in the brain. Until recently, this notion was dominant, despite the well-known facts such as lesion/symptom correlations observed in adults do not appear to the same degree for very young children with early brain injury (Lenneberg 1962). In general, without additional intervention, infants with early damage on one side/part of the brain usually go on to acquire abilities (language, vision, etc.) that are considered within the normal range.

Within recently published work on language, cognition and communicative development in children with focal brain injury (Elman *et al.* 1996; Bates *et al.* 1997; Stiles *et al.* 1998; Bates *et al.* 1999), the favorite viewpoint of brain organization for language has changed. Many scientist have taken a new consensus position between the historical extremes of *equipotentiality* (Lenneberg 1962) and *innate predetermination* of the adult pattern of brain organization for language (Stromswold 1995; Bates in press). However, there is still not a definite understanding of the levels of innateness and plasticity in the brain. Obviously, there is a lot of work to be done, and any advances will have a great impact for possible approaches of the many problems within clinical treatment or computational modeling.

Studies on aphasia constitute a significant part of the effort to understand the organization of the brain. The approach suggested here uses a recurrent neural network in order to classify interviewed subjects into normal or two different aphasic categories. The results obtained up to this point might be used in the clinical treatment of patients or classification of potential aphasics, but the proposed research continues into the direction of computational language modeling. Furthermore, the model is put into a perspective of integration of symbolic/sub-symbolic approaches. We suggest the use of neural preference Moore machines in order to extract certain aspects of the behavior of the network in deriving some neurobiological constraints of natural language processing.

The paper is structured as follows: First we give an outline about different forms of aphasia. Then we describe the recurrent neural network model and the specific aphasia corpus. Finally, we present detailed results on classifying Broca, Wernicke and normal patients.

Aphasia in the Brain

Aphasia is an impairment of language, affecting the production or comprehension of speech and the ability to read or write. Aphasia is associated with injury to the brain - most commonly as a result of a stroke, particularly in older individuals. It may also arise from head trauma, from brain tumors, or from infections. Aphasia may mainly affect a single aspect of language use, such as the ability to retrieve the names of objects, the ability to put words together into sentences, or the ability to read. More commonly, however, multiple aspects of communication are impaired. Generally though, it is possible to recognize different types or patterns of aphasia that correspond to the location of the brain injury in the individual case. The two most common varieties of aphasia are:

Broca's aphasia - This form of aphasia - also known as "non-fluent aphasia" - is characterized by a reduced and effortful quality of speech. Typically speech is limited to short utterances of less than four words and with a limited range of vocabulary. Although the person may often be able to understand the written and spoken word relatively well, they have an inability to form syntactically correct sentences, which limits both their speech and their writing.

Wernicke's aphasia - With this form of aphasia, the disability appears to be more semantic than syntactic. The person's ability to comprehend the meaning of words is chiefly impaired, while the ease with which they produce syntactically well-formed sentences is largely unaffected. For this reason, Wernicke's aphasia is often referred to as "fluent aphasia". Sentences are often long and syntactically quite good, but do not follow on from each other and can contain meaningless jargon.

Neural Network Models for Aphasia

For many prediction or classification tasks we need to take into account the history of an input sequence in order to provide "context" to our evaluation. One of the earliest methods for representing time and sequences in the processing of neural networks was to use a fixed sequence of inputs, presented to the network at the same time. This is the so-called sliding window architecture (Sejnowski and Rosenberg 1986). Each input unit (or more typically a group of input units) is responsible for processing one input in the sequence. Although this type of network has been used to good effect, it has some very basic limitations. Because the output units are only influenced by inputs within the current window, any longer-term dependencies for inputs outside of the current window are not taken into account by the network. This type of network is also limited to sequences of a fixed length. This is obviously a problem when processing variable length sentences.

One possible solution of the problem of giving a network temporal memory of the past is to introduce delays or feedback - Time Delay Neural Networks (Haffner and Waibel 1990; Waibel *et al.* 1989). Although this type of network is able to process variable-sized sequences, the history or context is still of fixed length. This means that the memory of the network is typically short.

One very simple and yet powerful way to represent longer term memory or context, is to use recurrent connections. Recurrent neural networks implement delays as cycles. In the simple neural network (Elman 1990), the context layer units store hidden unit activations from one time step, and then feed them back to the hidden units on the next time step. The hidden units thus recycle information over multiple time steps, and in this way, are able to learn longer-term temporal dependencies.

Another advantage of recurrent networks is that they can, in theory, learn to extract the relevant context from the input sequence. In contrast, the designer of a time delay neural network must decide a priori which part of the past input sequence should be used to predict the next input. In theory, a recurrent network can be used to learn arbitrarily long durations. In practice however, it is very difficult to train a recurrent network to learn long term dependencies using a gradient descent based algorithm. Various algorithms have been proposed that attempt to reduce this problem such as the back-propagation through time algorithm (Rumelhart *et al.* 1986a; 1986b) and the Back-Propagation for sequences (BPS) algorithm (Gori *et al.* 1989; Mozer 1989).

As one possibility for relating principles of symbolic computational representations and neural representations by means of preferences, we consider a so-called neural preference Moore machine (Wermter 1999).

Definition 1 (Preference Moore Machine)
A preference Moore machine PM is a synchronous sequential machine, which is characterized by a 4-tuple $PM = (I, O, S, f_p)$, with I, O and S non-empty sets of inputs, outputs and states. $f_p : I \times S \to O \times S$ is the sequential preference mapping and contains the state transition function f_s and the output function f_o. Here I, O and S are n-, m- and l-dimensional preferences with values from $[0,1]^n$, $[0,1]^m$ and $[0,1]^l$, respectively.

A general version of a preference Moore machine is shown to the left of figure 1. The preference Moore machine realizes a sequential preference mapping, which uses the current state preference S and the input preference I to assign an output preference O and a new state preference.

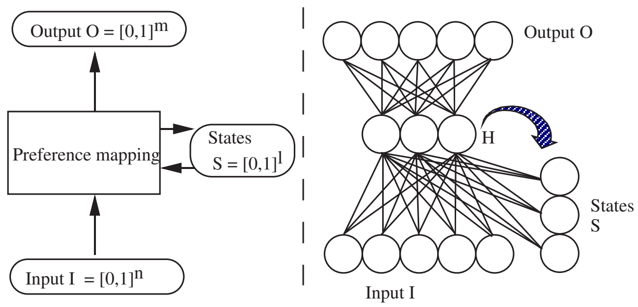

Figure 1: Neural preference Moore machine and its relationship to a simple recurrent neural network

Simple recurrent networks (Elman 1990) or plausibility networks (Wermter 1995) have the potential to learn a sequential preference mapping $f_p : I \times S \to O \times S$ automatically based on input and output examples (see figure 1), while traditional Moore machines or Fuzzy-Sequential-Functions (Santos 1973) use manual encodings. Such a simple recurrent neural network constitutes a neural preference Moore machine which generates a sequence of output preferences for a sequence of input preferences. Here, internal state preferences are used as local memory.

On the one hand, we can associate a neural preference Moore machine in a preference space with its symbolic interpretation. On the other hand, we can represent a symbolic transducer in a neural representation. Using the symbolic m-dimensional preferences and a corner reference order, it is possible to interpret neural preferences symbolically and to integrate symbolic preferences with neural preferences (Wermter 1999).

The CAP (Comparative Aphasia Project) Corpus

The CAP corpus consists of 60 language transcripts gathered from English, German, and Hungarian subjects. We summarize a description of this corpus based on the description in CHILDES database (Brinton and Fujiki 1996; Fujiki *et al.* 1996). Transcripts in the database for the English-speaking subjects are split into three groups:

(1) Broca's - characterized as non-fluent aphasics, displaying an abnormal reduction in utterance length and sentence complexity, with marked errors of omission and/or substitution in grammatical morphology.

(2) Wernicke's - aphasics suffering from marked comprehension deficits, despite fluent or hyper-fluent speech with an apparently normal melodic line; these patients are expected to display serious word finding difficulties, usually with semantic and/or phonological paraphasias and occasional paragrammatisms.

(3) A control group of normal subjects.

All of the subjects whose test results are presented in the database are right-handed and all had left lateral lesions. To exclude any ambiguity of the analysis, the patients with some additional non-aphasic diagnoses were excluded.

The language transcripts have been collected using a variation of the "given-new" picture description task of MacWhinney and Bates (MacWhinney and Bates 1978). Subjects were shown nine sets of three pictures as described by the sentences in table 1.

The morpheme coding of the corpus patterns is mapped, using the following syntactic descriptors: DET (determiner), CONJ (conjunction), N (noun), N-PL (plural form), PRO (pronoun), V (verb), V-PROG (progressive), AUX (auxiliary verb), ADV (adverb), PREP (preposition), ADJ (adjective), ADJ-N (numeric). Each of these descriptors is coded as a binary vector. Therefore, each sentence is presented as a sequence of descriptor vectors and a null vector to mark the end of a sentence. In fact the subjects from Broca's and Wernicke's groups do not give a simple sentence answer for many of the pictures. In this case, the answers are divided into subsequent sentences.

After each pattern is presented to the network, the computed and desired output are compared. The expected outputs correspond to a three-dimensional vector with values of true or false for each of the three subject classes. A particular value is set to one if the sentence so far (i.e. from the first word up to and including the current word) matches the beginning of any sentence from that subject class.

The CHILDES database contains test results for five subjects from each of the above three groups. The answers of the first three persons in each group are taken into the training set, and the answers from the other two construct the test set. Table 2 presents the distribution of examples in the two sets.

Experimental Results

A simple recurrent neural network is trained for 300 epochs. For one epoch, all the examples from the training set are presented, and the weights are adjusted after

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

Table 1: Picture series.

Subjects group	Training set	Test set
Normal	92	58
Wernicke's	182	135
Broca's	85	68

Table 2: Number of different sentences in the training and test sets.

each word. After the training is completed, the network is tested on the training and test sets. The results presented in tables 3 and 4 suggest encouraging results.

Subject group	% of answers classified as		
	Normal	Wernicke's	Broca's
Normal	63	29	8
Wernicke's	5	90	5
Broca's	9	18	72

Table 3: Results from the training set.

Subject group	% of answers classified as		
	Normal	Wernicke's	Broca's
Normal	65	19	16
Wernicke's	24	63	13
Broca's	16	19	66

Table 4: Results from the test set.

As we can examine, the model is able to provide a distinction between subjects with different forms of aphasia, based on syntactic information. On a level of a particular sentence, the information is not sufficient, but based on the whole set of answers in the patient's test, we are able to assign the subject to a correct group.

Future Work

We have described ongoing work on distinguishing aphasia forms with recurrent networks. The integration of symbolic/sub-symbolic techniques will extend the range of the current research. An integration of neural preference Moore machines provides the symbolic interpretation and allows further, more detailed analysis of the network processing. In addition, such an analysis may suggest some architectural or representational constraints of language processing in the brain.

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