*Proceedings of the Second International Conference on the Cognitive Science of Natural Language Processing,* pp.4-11.
Dublin, Ireland: Dublin City University.

# Connectionist Modelling of Reading Aloud

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A new class of neural network models of reading aloud are presented. Unlike previous models, they are not restricted to monosyllabic words, require no complicated input-output representations such as Wickelfeatures and require no pre-processing to align the letters and phonemes in the training data. The best cases are able to achieve 100% performance on the Seidenberg & McClelland training corpus, in excess of 90% on pronounceable non-words and on damage exhibit symptoms similar to acquired surface dyslexia. Their simplicity, performance and room for improvement make them a promising basis for the grapheme-phoneme conversion route of a realistic dual route model of reading.

## Introduction

There are many processes involved in the act of 'reading aloud' and we are clearly a long way from being able to construct a realistic model of them all. Any complete reading system must (at least) be able to :

1. recognise whole words and groups of words, parse them, relate them to their meanings and output their sounds, and

2. read aloud unknown words or pronounceable non-words (i.e. have a series of rules that simply convert text to phonemes),

and there is currently a lively debate concerning the exact processes underlying these abilities. One camp (recently championed by Coltheart, Curtis & Atkins, 1992) argues that they can only be described by a dual route model, with one route that acts as a lexicon (necessary to output phonemes for irregular/exception words which do not follow the rules and to provide a contact point for traditional natural language processing) and another route consisting of the letters to phonemes rules (necessary for new words or pronounceable non-words). The other camp (as exemplified by Plaut, Seidenberg & McClelland, 1992) suggest that a single route may be sufficient and have constructed explicit neural network models of reading that are able to learn the words (including exception words) in their training data and also read new non-words with accuracies comparable to human subjects. Although it seems unlikely, at this stage, that a single route model will be able to account for all aspects of human reading abilities (Coltheart et al., 1992), there is considerable evidence that the two routes of the dual route model can not be totally independent (Humphreys & Evett, 1985). There are several directions from which we can attack this problem. The approach we propose here is to construct explicit connectionist models of text to phoneme conversion and then examine how well these can fit in with more complete models of reading.

The first thing that has to be decided for any model of text to phoneme conversion is the choice of representation to use for the inputs (letters) and outputs (phonemes). If there were a one-to-one correspondence between the letters and phonemes of every word, it would be fairly easy to set up a neural network to map from letter strings to phoneme strings. Unfortunately, however, the mapping is many-to-one (up to four letters can map to one phoneme in English, e.g. 'ough' → /O/ in 'though'), so more complicated models are necessary. We use the notation and terminology of Seidenberg & McClelland (1989) throughout.

One of the first successful neural network systems to get round this problem was NETtalk by Sejnowski & Rosenberg (1987) who simply pre-processed the training data by inserting special continuation (i.e. no output) characters into the phoneme strings to align the letters and phonemes. For many, this degree of pre-processing is considered unacceptable.

A more sophisticated model by Seidenberg & McClelland (1989) used a system of distributed Wickelfeatures in which each letter and phoneme string is split into sets of triples of characters (Rumelhart & McClelland, 1986). This certainly bypasses the problem of aligning the letters and phonemes, but makes the interpretation of the networks output difficult and presents difficulties in understanding the nature of the internal representations. This model is also restricted to mono-syllabic words and performs poorly on non-words.

A more recent neural network model by Plaut et al. (1992) uses 108 orthographic input units (one for each of the Venezky graphemes occurring in the initial consonant, vowel and final consonant clusters) and 57 phonological output units. This model does very well at learning the training data and at reading non-words but is still restricted to mono-syllabic words.

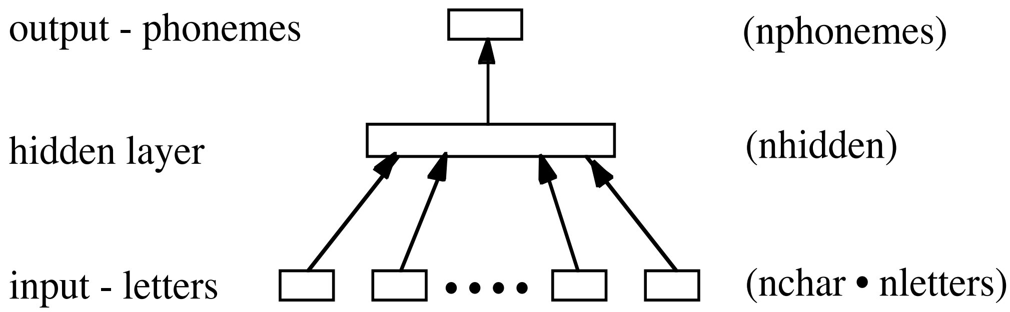
Meanwhile, Coltheart et al. (1992), as part of their dual route model, developed a rule based non-neural network system which had good success in reading non-words, but (by construction) was poor at reading the non-regular words in the original training set.

The class of neural network models presented in this paper might be considered to be a neural network implementation of this Grapheme Phoneme Conversion (GPC) Rule system of Coltheart et al. (1992). However, given that an exception word mapping can be thought of as a very low frequency high powered rule (i.e. a rule that is activated only for one specific word and over-rides all other potentially useful rules) such a model should be able to handle exceptional words as well. Regular words will be pronounced according to simple rules, exception words will be pronounced according to complicated special purpose rules (effectively a lexicon) that must over-rule the simpler rules. There will clearly be a continuous spectrum between these two classes of words and since there are very few (if any) 'exception' words that do not contain any regular features at all, the need for true lexical entries will be minimal. The success of the model depends on the network maximizing its use of simple rules whilst minimizing its use of special purpose rules. In this way, when presented with new words or non-words, none of the special purpose rules will fire and the network will output phonemes according to a full set of regular (GPC) rules, yet it will still be able to pronounce the exceptional words it has been trained on.

## The Models

The basic model consists of a standard fully connected feedforward network with sigmoidal activation functions and one hidden layer set up in a similar manner to the NETtalk model of Sejnowski & Rosenberg (1987). The input layer consists of a window of *nchar* sets of units, each set consisting of one unit for each letter occurring in the training data (i.e. 26 for English). The output layer consists of one unit for each phoneme occurring in the training data (i.e. about 40 units).

The networks were trained using the back-propagation gradient descent learning algorithm (Rumelhart, Hinton & Williams, 1986) with the extended Seidenberg & McClelland training corpus of 2998 monosyllabic words consisting of the original Seidenberg & McClelland (1989) set plus 101 other words missing from that set (Plaut et al., 1992). About 25% of the training data was presented in each epoch in random order with the same frequency distribution as in Seidenberg & McClelland (1989).




The input words slide through the input window which is *nchar* letters wide, starting with the first letter of the word at the central position of the window and ending with the final letter of the word at the central position. Each letter activates a single input unit. If there were a one-to-one correspondence between the letters and the phonemes, the activated output phoneme would then correspond to the letter occurring in the centre of the window. Since there can be a many-to-one correspondence between the letters and phonemes, some of the outputs must be blanks (i.e. no phoneme output). It is the problem of not knowing where to put the blanks in the training data that has hampered progress with this type of model in the past.

The solution proposed here is to allow the set of phonemes corresponding to each word in the training data to be padded out with blanks (to the same number of phonemes as there are letters in the word) in all possible ways. If there are $nl$ letters and $np$ phonemes, then there are $ntarg = nl! \,/\, np!\,(nl - np)!$ ways that this can be done. Clearly, we only want the network to train on one of these *ntarg* possible targets. The surprising thing is that (with a suitable error measure) by calculating for each input word the total error corresponding to each of the possible targets and only propagating back the error from the target with the least error, the network is (with a suitably diverse set of training words) able to *learn* which is the appropriate target for each word.

For example, consider the word ‘ace’ and the corresponding phonemes /As/. This training example will be presented $nl = 3$ times, each with $ntarg = 3$ possible target outputs:

| presentation | inputs | target outputs | | |
|---|---|---|---|---|
| 1. | `- - - a c e -` | A | A | - |
| 2. | `- - a c e - -` | s | - | A |
| 3. | `- a c e - - -` | - | s | s |

For each of the three input presentations the error is calculated for each of the three target outputs. The sum of the errors for each target over the three input presentations is then computed and the target with the minimum total error is used to update the weights in the appropriate manner. Given small random initial weights and a representative set of training words, common potential rules such as ‘c’ → /s/ will dominate the weight changes over others such as ‘c’ → /A/ and the network will automatically settle into a useful set of targets including ‘ace’ → /As-/ rather than /A-s/ or /-As/.

For each word (or sub-word) presentation, the output phoneme of the network is simply defined to be the phoneme corresponding to the output unit with the highest activation. More sophisticated versions in the future will undoubtedly benefit from the imposition of more complicated decision criteria, clean-up units, etc. Another important design choice that has to be made here is whether to have a separate output unit corresponding to a blank (i.e. no phoneme) or simply have some threshold such that if no output activation exceeds that threshold then the network output is deemed to be a blank. In order to make this decision, networks adopting both approaches were constructed and their results compared. It was found that networks with explicit blanks performed slightly better.

One problem that needs to be overcome with this model and training data is that some letters (namely ‘j’, ‘g’, ‘x’) can give rise to more than one phoneme (namely /dz/, /dz/, /ks/) and hence some words can have fewer letters than phonemes (e.g. ‘cox’ → /koks/). In order to solve this problem without complicating the model, in these cases the combinations /dz/ and /ks/ were replaced by additional ‘phonemes’ /J/ and /X/ respectively, bringing the total number of phonemes up to forty. This recoding, however, is not necessary in more sophisticated versions of this model (Bullinaria, 1993).

The small initial weights were chosen randomly with a rectangular distribution in the range $-0.1$ to $+0.1$. After some experimentation, the back-propagation learning rate was fixed at 0.05 and the momentum factor at 0.9. In order to prevent activations getting stuck hard wrong (where the error propagated back is zero) targets of 0.1 and 0.9 are often used rather than 0 and 1 (as in Seidenberg & McClelland, 1989). However, a few initial trial runs suggested that slightly better results were achieved using a Sigmoid Prime Offset (Fahlman, 1988) of 0.1 instead, and so this approach was used throughout. Experiments with weight decay were inconclusive and so none was used. Over-learning was controlled by not propagating back the error signal for words that already had the correct phoneme outputs and a total error less than some threshold *errcrit*.

## Results from the Simulations

For each simulation, against the number of training epochs (on a logarithmic scale), were plotted the percentages learnt correctly and mean square errors for the full set of training data plus various interesting subsets (homographs, regular words, high/low frequency exceptions, etc.). To test the networks generalization ability (i.e. its success at learning the GPC rules) the percentages of three sets of non-words that were pronounced 'acceptably' and the corresponding errors were also plotted.

As in Plaut et al. (1992), the three sets of non-words used were the regular non-words and exception non-words of Glushko (1979, Experiment 1) and the control non-words of McCann & Besner (1987, Experiment 1). The allowable pronunciations of these non-words were derived from the training data-base by matching word segments (particularly rimes) in the non-words with the same segments in the training data and constructing possible non-word pronunciations by concatenating the pronunciations of the segments from the training data. For the regular non-words this typically led to a single allowable pronunciation (e.g. 'dold' → /dOld/ by analogy with 'told' → /tOld/), but for the exceptional non-words there are often several allowable pronunciations (e.g. 'sost' → /s*st/ as in 'cost', → /sOst/ as in 'most' , → /s^st/ as in 'dost').

Due to the large amount of processing power required for these simulations, only 25 fairly small runs have so far been carried out and it is often difficult to distinguish real improvements caused by parameter or architecture changes from statistical fluctuations. A detailed analysis of how the models' performance varies with the window size, number of hidden units, *errcrit*, etc., what structures are actually being represented in the hidden units, the relationship between errors and naming latencies, developmental dyslexias and how the model responds to different types of damage will be presented in a necessarily longer paper elsewhere (Bullinaria, 1993). Here we will just make a few general comments and plot some results from one typical successful run.

Since the Seidenberg & McClelland corpus contains 13 pairs of homographs it is clear that the network can never achieve total success at learning this training data. Experiments were therefore carried out on the use of context flags to resolve these ambiguities. As a preliminary investigation, this was implemented by introducing a single extra character into the input alphabet and appending that character to the least regular input word of each pair of homographs. This not only allowed the network to achieve 100% success rate on the homographs (compared with a maximum of 50% before) but also seemed to improve its performance on certain non-homographs as well. That such a simple flag works so well also gives us hope that similar flags could be used to flip the network between accents and languages as effortlessly as in humans and also that we can have simple and efficient communication between the two routes of a dual route model.

Networks with a window size of 9 characters and as few as 40 hidden units were able to learn all but one of the training examples, namely 'though' → /DO/. The reason the network fails on this word is that the training data also includes the word 'thought' → /T*t/ in which the sub-word 'though' has to be pronounced as /T*/ and unless the input window is large enough to have the final 't' in the window while the initial 't' is in the centre of the window, the network has no way of resolving the ambiguity. By increasing the window size to 13 this long range dependency can be handled and the network achieves 100% success rate on its

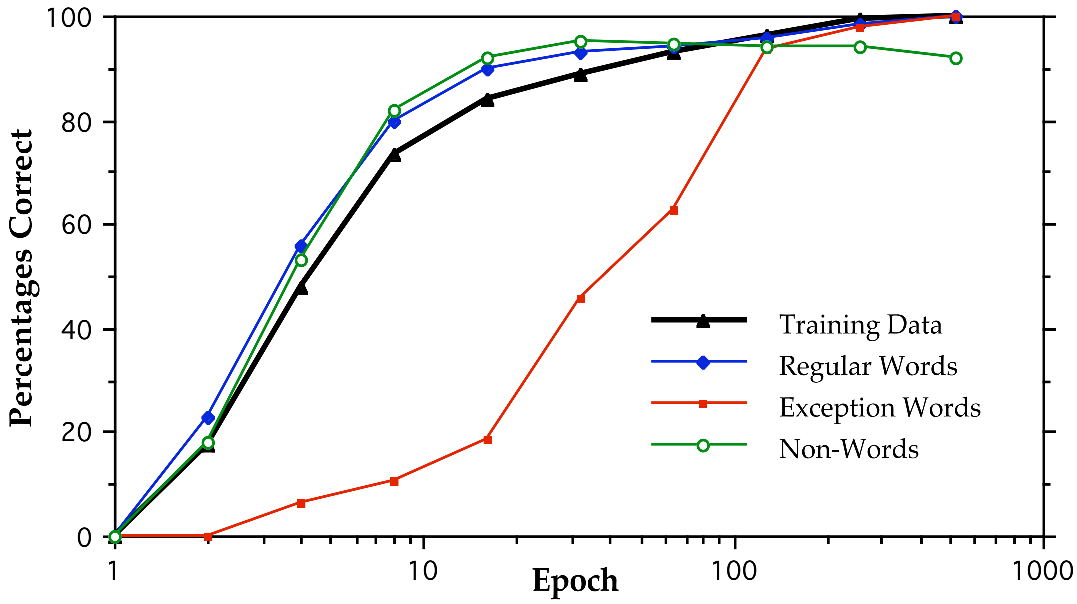



**Figure 1. Typical Learning Curves.**

training data. To confirm the networks' capability of handling long range dependencies and also its ability to deal with more complex words, some runs with the words 'photographic' → /fotOgrafik/ and 'photography' → /fot*grafE/ incorporated into the training data were carried out. Each of these words contain the letter 'o' pronounced in two different ways and the pronunciation of the second 'o' is determined only by letters at least six characters away. With a window size of 13 the network was able to learn both words without any difficulty. With a window size of 11 (for which the crucial 'i' and 'y' fall outside the window while the problematic second 'o' is in the central position) the network failed to learn the two words.

Figure 1. shows the learning curves for a typical network with 120 hidden units, a window size of 13 characters, explicit 'blanks' in the output units, *errcrit* = 0.01 and a context flag to resolve homograph ambiguities. The generalization performance peaks at about 30 epochs and then falls as the exception words are learnt. The network eventually achieved 100% performance on the training data and for non-words plateaued at 95.3% for regulars, 93.0% for exceptions and 92.5% for controls. Comparisons with other models are complicated by different authors using different non-word sets and scoring criteria, so bearing this in mind, the Seidenberg & McClelland (1989) model achieved 97.3% on the training data and about 65% on Glushko non-words, Plaut et al. (1992) achieved 99.9% and 97.7%, Coltheart et al. (1992) achieved about 77% and 98% and for human subjects we would typically have about 100% and 96%.

Although our networks generally performed fairly well, and many of the non-word errors would be acceptable under more generous criteria of acceptability (e.g. 'wuff' → /wuf/ and 'wosh' → /w*S/ are counted as wrong by the above rules), there still remain a few errors of the kind humans would never make (e.g. 'zute' → /hyt/). Whether these problems can be removed by the introduction of recurrent connections, clean up units, different learning algorithms/parameters is not clear at present. However, for small networks it was found that increasing the number of hidden units improved generalization. It was also noticed that if smaller training sets were used, then obviously incorrect grapheme-phoneme correspondences could

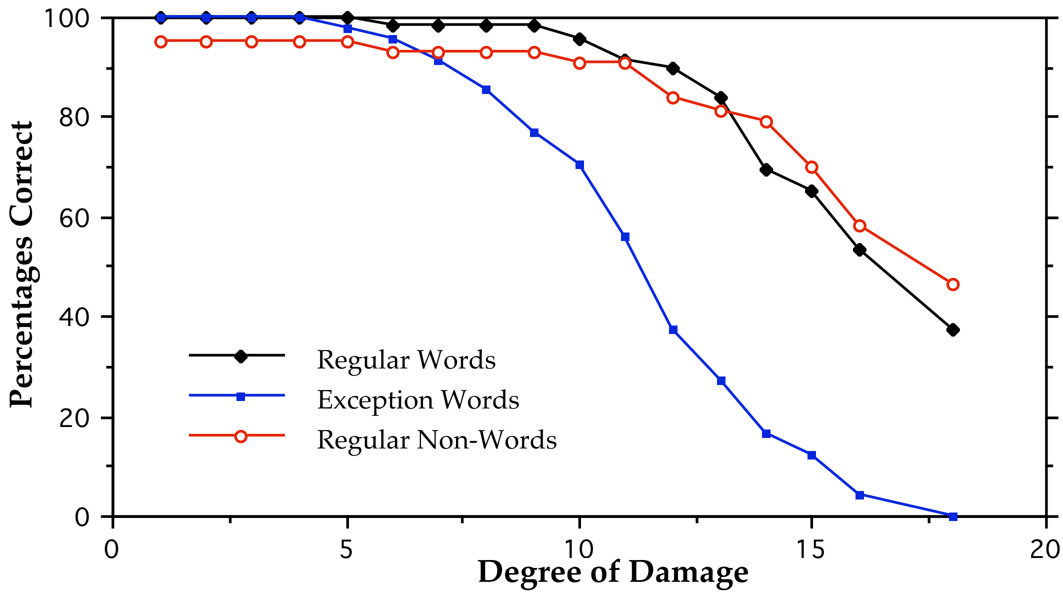



**Figure 2. Typical Damage Curves.**

be learnt (e.g. 'ace' → /-As/ instead of /As-/) without affecting the output performance on that training set. It is likely, therefore, that simply using larger networks and training sets could further improve our performance on non-words.

## Discussion

An important method of constraining cognitive models is to examine their performance after damage (e.g., Coltheart et al., 1992). Of particular importance for models of reading are two forms of acquired dyslexia: Patients with phonological dyslexia exhibit a dissociation between word and non-word naming - there can be complete failure to read non-words whilst maintaining around 90% success on words (Funnell, 1983). Patients with surface dyslexia exhibit a dissociation between regular and exception word naming - for example, 90% success on low frequency regular words against 40% on low frequency exceptions (Bub, Cancelliere & Kertesz, 1985) and 80% on regular words against 35% on very irregular words (Shallice, Warrington & McCarthy, 1983).

Since no form of damage to our model seems to be able to produce the loss of rules (i.e. non-words) but not the words (nor even the high frequency exceptions) we should not consider it to be a realistic single route model. Phonological dyslexia must presumably still be explained by losing the GPC route, but not the lexical/semantic route, of a dual route model (Coltheart et al., 1992). It would seem appropriate, therefore, to consider our model to be an implementation of the GPC route of a dual route model. However, given our models inherent success with non-words, losing the lexical/semantic route but not the GPC route is not enough to explain surface dyslexia. We must, at the same time, lose the exceptions but not the rules in our GPC route. Fortunately, a form of damage whereby all the weights (i.e. synaptic strengths) are globally reduced in magnitude seems to do just that. In Figure 2. is plotted (for the same network as Figure 1.) the network performance as its weights are reduced by successive amounts of 0.05. We see that the exception words are preferentially lost over the regular words, so that at the point where the weights have been reduced by a total of 0.6 we have regular word performance at

90% compared with exception word performance at 37%. The exact percentages seem to vary somewhat with different network parameters, in particular the number of hidden units, but they are generally not far from those found in human patients.

In conclusion then, a class of neural network models have been presented which, given their simplicity, performance and room for improvement, seem to be promising candidates for the GPC route of a realistic dual route model of reading.

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