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A Neural Network Model of Lexicalization for Simulating the Anomic Naming Errors of Dementia Patients

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Abstract

Word-finding difficulty (anomia) is the most common linguistic deficit in dementia. It is often measured by picture naming tasks as naming a picture taps all the major processes in word production, i.e., activation of a concept, retrieval of lexical-semantic information on that concept, retrieval of the corresponding word form and articulation. Naming and naming errors have extensively been simulated by neural network models of lexicalization (see e.g. [1,2]). A common feature of these models is that they are static, i.e. non-learning. However, naming is a dynamic process that changes as a function of normal learning or re-learning after neural damage. These important patterns cannot be caught by the static models of lexicalization. Therefore we have developed a learning model of lexicalization based on multi-layer-perceptron (MLP) neural networks. We tested the model by fitting it to the naming data of 22 Finnish-speaking dementia patients and 19 neurologically intact control subjects. The tests showed an excellent fit between the model's and the subjects naming response distributions. Thus our model seems be suitable to simulate naming disorders of dementia patients.

Keywords:
Neural network, word production problems, dementia.

Introduction

Anomia (word-finding difficulty) is the most common linguistic deficit in dementia. This difficulty is often documented by a picture naming task where the subject is to name (i.e., say aloud) single pictures. The main reason for the popularity of this method is the fact that this simple task calls for all the major processing stages involved in word production: activation of a concept, retrieval of lexical-semantic information on that concept, retrieval of the corresponding word form, and articulation. Besides a quantitative measure (number correct), the types of errors produced during picture naming are of interest as they may shed light on the underlying reasons of a patient's anomia. Examples of commonly encountered error types include ***semantic errors*** (cat → dog), ***formal errors*** (cat → cap), ***neologistic (nonword) errors*** (cat → neet) and ***omission errors*** (patient utters nothing or says "I don't know" etc.).

Leaving the visual perception of the picture and the articulation of the word aside, naming process can be considered as a process of ***lexicalization***. During lexicalization we translate a semantic representation (meaning) of a target concept into its phonological representation (sound structure). It is widely accepted that lexicalization is a two-stage process [3]. In the first phase we retrieve an abstract lexical-semantic representation of the word (lemma). During the second phase the retrieved lemma is translated to the corresponding phonological word form (lexeme).

Although researchers commonly agree on the two phases involved in lexicalization, the relationship between these phases is still being disputed. The Discrete Two-Stage (DTS) theory of lexicalization states that the two phases of lexicalization are independent, all lexical-semantic processing is performed before phonological processing, and that in a task like picture naming only the single selected lemma is translated into its corresponding lexeme [1]. The Interactive Activation (IA) theories of lexicalization propose that lexical-semantic and phonological processing overlap in time and can influence each other [2].

Naming and naming errors have been simulated by both DTS and IA neural network models of lexicalization (see e.g. [1,2,4] for models and [3,4] for discussion). A common feature of these models is that they are static, i.e. non-learning. However, there are important aspects of naming that cannot be modelled by the static models of lexicalization. These include word learning in children and re-acquisition of naming ability after brain damage due to spontaneous recovery and/or systematic rehabilitation.

We have previously constructed and evaluated a DTS model for simulating naming errors of Finnish-speaking aphasia patients suffering from focal brain lesions [5,6]. The critical difference to the previous models of lexicalization is that our model is implemented using MLP neural networks, i.e., it is a learning model. Here we extend our research by fitting the model to the naming data of 22 Finnish-speaking dementia patients suffering from either probable Alzheimer's disease (AD) or vascular disease (VaD), and 19 neurologically intact control subjects described by Laine et al. in [7]. Even though episodic memory deficits dominate the symptomatology in dementia, anomia is also common in these patients. The nature of anomia in dementia has received considerable research interest, and the prevailing view has been that semantic disorders play a central role in the patients' naming problems.

The model

The architecture of our simulation model is shown in Figure 1. Based on the DTS theory of lexicalization, the model consists of two subnetworks: lexical-semantic network and phoneme network. Lexical-semantic network simulates the lemma access and phoneme network simulates the phonological access. The phoneme subnetwork is further divided into separate consonant and vowel networks since in both normal and pathological speech error data, consonant-vowel substitutions are non-existent. All networks are auto-associative, i.e. their target outputs are same as their inputs. The number of hidden layers and nodes in them was decided experimentally (see [5]).

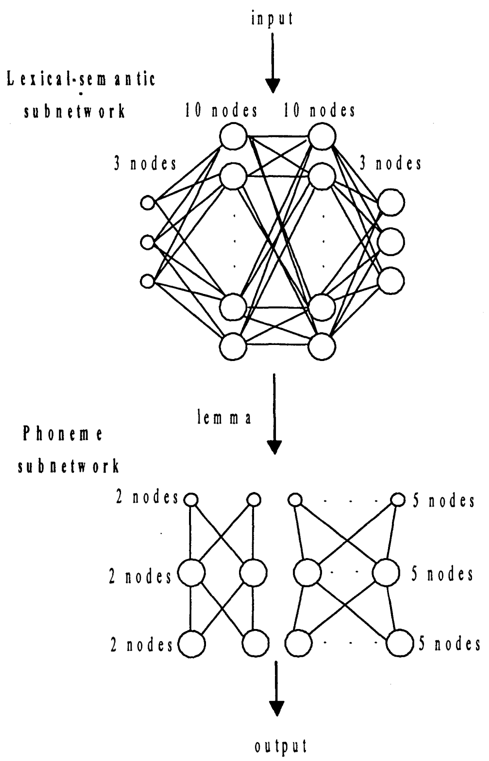

Figure 1 - Architecture of the simulation model

Because all three subnetworks of the model are standard MLP neural networks with sigmoid activation function, normal computation rules and equations of MLP neural networks were applied (see e.g. [8]). However, to simulate disturbed word production we added a random noise parameter $\acute{a}e_{ij}$ to every weight w_{ij} between the nodes i and j. The parameter e_{ij} is derived from normal distribution N(0,1) and $\acute{a}$ is a positive scaling factor. The total input v_i for node i is then calculated as in Equation (1), where x_j is an output of node j connected to the node i and n is the number of the nodes in the current layer (x_0=1 is a bias scalar)..

$$v_i = \sum_{j=0}^{n} (w_{ij} + \alpha e_{ij}) \cdot x_j$$

Naming errors can now be simulated by increasing the scaling factor $\acute{a}$ in Equation (1). This randomizes the outputs of the network. For instance severe anomic disorders can be simulated with large values and slight disorders with small values of $\acute{a}$. In the model there is a separate scaling factor for the lexical-semantic subnetwork ($\acute{a}_L$ to simulate semantic disorders) and for the phoneme subnetwork ($\acute{a}_P$ to simulate phonological disorders).

To simulate omissions we applied a threshold value τ between the subnetworks. The threshold discards outputs of the lexical-semantic network that are too far from any word taught to it. Let **o** be the output vector of lexical-semantic network and **n** the nearest vector (in the Euclidean sense) to **o** taught to the model. The thresholded result **r** of lexical-semantic network is then calculated with Equation (2), where d_E(**o**,**n**) is an Euclidean distance between vectors **n** and **o** and c is a scaling factor. During the simulations we set c = 100.

Eq. (2)

$$\mathbf{r} = \begin{cases} \mathbf{n}, & \text{if } \tau \le \dfrac{1}{c \cdot d_E(\mathbf{o},\mathbf{n})}, \quad d_E(\mathbf{o},\mathbf{n}) > 0, \\ \mathbf{n}, & \text{if } d_E(\mathbf{o},\mathbf{n}) = 0, \\ \text{otherwise undefined} & \end{cases}$$

The output of the model was interpreted as an omission when the output vector **r** of the lexical-semantic subnetwork becomes undefined.

Based on the previous equations the result of the whole network is computed as follows:

1. Compute the output vector **o** of the lexical-semantic network.
2. Use the threshold τ as in Equation (2) to decide the result **r** of the lexical-semantic network (lemma).
3. Compute the lexeme by processing the phonemes corresponding to the selected lemma in the phoneme network one at a time.

A more detailed description of the model and the coding of its inputs and outputs is available in [5,6].

Results

We tested the model by fitting it to the naming data of 12 Finnish-speaking probable Alzheimer's disease patients, 10 vascular dementia patients, and 19 neurologically intact control subjects described by Laine et al. in [7]. The subjects' naming distributions were based on the half of the items (i.e. 30) in the Finnish version of the Boston Naming Test [9] but Laine et al. [7] allowed 45 seconds for spontaneous naming to produce enough scoreable data. Thus most subjects' error distribution is based on over 30 answers.

To automatize the error classification we reduced the errors to three error classes: omissions, semantic errors and other errors. The following rules were applied to the error classification:

1. An output was an omission if the lexical-semantic subnetwork generated no response to a given input word.
2. An output was a semantic error if an output word of the lexical-semantic subnetwork was different from its input word.
3. An output was other error if an output word of the phoneme subnetwork was different from its input word, i.e. output of the lexical-semantic network.

Table 1: Empirical naming tests results and corresponding average results of the simulations

Patient	α_L	τ	α_P	Correct %		Semantic %		Other %		Omission %	
				Patient	Simul.	Patient	Simul.	Patient	Simul.	Patient	Simul.
AD1	0.225	0.138	0.104	25.4	26.3	62.7	61.9	11.9	11.6	0.0	0.1
AD2	0.163	0.115	0.082	37.1	38.0	54.8	54.7	8.1	7.3	0.0	0.0
AD3	0.324	0.152	0.337	0.0	4.0	85.3	81.3	14.7	14.7	0.0	0.0
AD4	0.050	0.049	0.043	76.7	76.9	23.3	22.9	0.0	0.0	0.0	0.2
AD5	0.312	0.178	0.149	14.0	14.8	68.0	66.6	18.0	18.4	0.0	0.2
AD6	0.054	0.088	0.046	80.6	81.6	16.1	15.9	3.2	2.5	0.0	0.0
AD7	0.080	0.107	0.080	62.5	63.9	25.0	24.0	6.3	5.8	6.3	6.2
AD8	0.153	0.091	0.077	40.0	41.1	54.0	53.1	4.0	3.5	2.0	2.3
AD9	0.105	0.101	0.081	50.0	51.5	32.5	32.0	5.0	4.7	12.5	11.9
AD10	0.157	0.118	0.079	37.8	38.7	53.3	53.0	8.9	8.1	0.0	0.2
AD11	0.069	0.307	0.250	9.8	10.5	73.2	71.9	9.8	10.4	7.3	7.2
AD12	0.098	0.170	0.091	43.2	41.7	27.0	28.1	13.5	14.1	16.2	16.1
VaD1	0.056	0.299	0.237	8.9	8.3	75.6	75.8	8.9	8.5	6.7	7.3
VaD2	0.039	0.050	0.050	62.5	62.6	37.5	35.8	0.0	0.0	0.0	1.6
VaD3	0.112	0.097	0.243	46.5	46.3	30.2	29.6	18.6	19.6	4.7	4.4
VaD4	0.045	0.145	0.118	42.6	42.4	53.2	54.2	2.1	1.7	2.1	1.7
VaD5	0.049	0.089	0.197	60.0	58.9	32.5	34.1	7.5	7.0	0.0	0.0
VaD6	0.044	0.113	0.209	48.7	48.6	43.6	44.4	7.7	7.0	0.0	0.0
VaD7	0.048	0.099	0.218	54.1	56.5	35.1	35.5	10.8	8.0	0.0	0.1
VaD8	0.048	0.074	0.095	73.0	74.3	27.0	25.7	0.0	0.0	0.0	0.0
VaD9	0.069	0.085	0.134	64.1	65.8	30.8	29.6	2.6	2.4	2.6	2.2
VaD10	0.049	0.072	0.167	70.0	68.8	23.3	23.6	6.7	7.6	0.0	0.0
Control	0.018	0.050	0.076	78.8	79.9	17.6	18.6	2.6	2.0	0.0	0.0

If the model first gave a semantic error and then other error, this was simply posed as other. To assess the generality of the results we trained 11 networks for each patient with different random starting weights. The training set consisted of 279 Finnish nouns, most of them from our data, but 89 were translated from the corpus of Snodgrass and Vanderwart [10]. During the simulations each word was used as a target for five times. Thus the naming distributions produced by the model are based on 1395 words. This smoothed out the results of the noisy model and allowed us to utilize a formal fitting process (see [6]).

Actual picture naming error patterns of individual patients and corresponding averaged simulation results are presented in Table 1 ("control" is averaged over all neurologically intact control subjects and corresponding simulation data). On the average, the linguistic abilities of VaD patients (57.1 % correct answers) were better preserved than those of AD patients (38.9 % correct answers). The differences between the patient groups are due to semantic errors, which AD patients had considerably more than VaD patients (53.7 % vs. 33.8 % on the average). In other errors (AD 8.5 %, VaD 7.1 %) and in omissions (AD 0.0 %, VaD 0.0 %) the average differences between the patient groups are slight.

The results in Table 1 show that the model's fit to the simulated data was excellent. Although the results in the Table 1 represent the average, the variations between tests were slight, a few percent typically. The differences between the patient data and the simulated data were tested with the χ^2 test. We did not find a statistical difference between them in any patient case. Consequently, the model seems to be capable to simulate naming errors of Finnish-speaking dementia patients.

In the Figure 2 the subjects are plotted with respect to the simulation parameters α_L, α_P, and τ. The squares represent AD patients, the circles VaD patients and the diamonds represent the intact control subjects. The intact control subjects form a tight cluster, but the clusters of AD and VaD patients are more dispersed. Generally, according to the noise parameter α_L, the VaD patients are closer to the intact control subjects than AD patients (see Table 2). This is the consequence of the fact that the simulated AD patients tend to make more semantic errors than the simulated VaD patients. On the other hand AD patients are usually closer to the intact control subjects with respect to the noise parameter α_P. The differences between the AD and VaD patients are not significant with respect to the threshold τ.

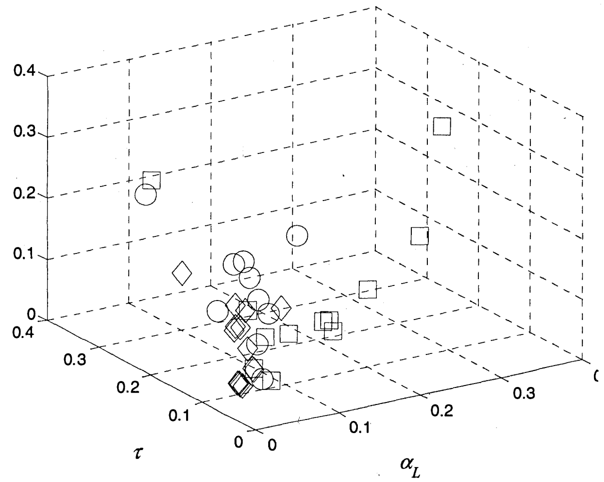

Figure 2 - Plotting the subjects with respect to the simulation parameters

Discussion

We have presented a neural network model for simulating the anomic naming errors of Finnish-speaking AD and VaD patients. The tests showed that the model was able to simulate the naming distributions of different dementia patients as well as those of intact control subjects very precisely. This indicates that our simulation model could be useful also in the field of dementia research. The patient data in Table 1 and the medians of the simulation parameters in Table 2 suggest that on the average linguistic abilities were better preserved in VaD patients than in AD patients (see also [7]). The clearest distinction between the patient groups can be made in terms of semantic errors, which AD patient had considerably more than VaD patients. This distinction is present also at Table 2, in which AD patients have averagely greater noise parameter $\acute{a}_L$ values than VaD patients.

Table 2: Medians of the simulation parameters

Group	α_L	t	α_P
AD	0.129	0.116	0.082
VaD	0.048	0.093	0.182
Control	0.018	0.050	0.076

Our model was successful in simulating the naming patterns of AD and VaD patients as well as those of intact control subjects. There are some flaws in the model that should be addressed in the future. For instance, the model did not simulate visual perception of the picture that might be impaired in AD patients (but see [11] for an alternative explanation). Also the classification of the errors produced by the model should be specified to separate different types of phonological errors from each other. This would give further information about the model's actual abilities to simulate various naming response patterns in anomia. Moreover, there are various robust patient data findings that are problematic for any DTS model of lexicalization [4].

In this study we simulated the naming patterns of dementia patients. Our model was based on widely applied MLP neural network architecture and thus it opens the way for modelling recovery and rehabilitation of patients. This has not been possible with traditional non-learning models of lexicalization. Of course, the learning capability is of secondary importance in the present study. However, the strive towards more realistic simulations of linguistic performance necessitates models that can learn as humans do.

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