

# Exploring Lexical Network Development in Second Language Learners

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## Abstract

This study explores how neural network models can simulate word production in second language (L2) learners. A neural network was trained to simulate L2 word production using a variety of word properties related to connectionist networks (hypernymy, polysemy, concreteness, and meaningfulness). The study demonstrates that a neural network can produce words to a similar degree as L2 learners. The findings are important for theories of L2 lexical growth and production.

## Introduction

Theories of connectionism and their links to artificial neural networks (ANN) are relatively new. While neural network models exploring lexical acquisition in bilingual learners are common, few researchers in second language (L2) acquisition have examined neural network approaches to lexical production. When L2 neural network models have been explored, they have been in the absence of actual linguistic features (Meara, 2006) or through the use of non-learning networks (Meara, 2007).

Our purpose is to demonstrate how word properties (both conceptual and psycholinguistic) that are linked to network models can be used to simulate word production by L2 learners. We first conduct a corpus analysis of both L1 and L2 spoken discourse to select produced and unproduced words. We provide word property values for these words from WordNet and from the Medical Research Council (MRC) psycholinguistic database. We then construct an ANN with the outputs for the words as either produced or unproduced and test whether the network can correctly categorize the words based on word properties. The study demonstrates that ANNs can categorize produced and unproduced words to a significant degree.

## L2 Lexical Acquisition

L2 lexical production is crucial because the inaccurate production of lexical items is a key factor in global errors that inhibit communication (Ellis, R., 1995) and lexical production is strongly related to academic achievement (Daller, van Hout, & Treffers-Daller, 2003). Until recently, most studies that have examined L2 lexical acquisition and production have focused on broad measures of lexical

growth such as lexical accuracy, lexical frequency, and lexical diversity (Polio, 2001). These studies, while important, generally touch only on surface level linguistic features and fail to provide a connectionist perspective of L2 lexical knowledge.

Connectionist models of lexical acquisition are premised on notions of lexical networks. Lexical networks extend theories of lexical acquisition by considering the strengths of interconnections between words and not simply the memorization of words, their definitions, orthography and sound patterns. Theories of lexical networks support the notion that words interrelate with other words to form clusters of words that act categorically. These clusters connect to other clusters and other words, until entire lexicons are developed based on interconnections. Connections between words allow newly acquired words and phrases to be easily assimilated within these networks because new words are not learned in isolation, but through links to already learned words. As learners progress lexically, they build lexical networks that are strengthened by differentiating sense relations between words and within words (Haastrup & Henriksen, 2000).

A few recent studies have analyzed the development of L2 lexical networks (e.g. Crossley, Salsbury, McCarthy, & McNamara, 2008; Crossley, Salsbury, & McNamara, in press; Schmitt, 1998), but such studies have been relatively rare. These studies have demonstrated that L2 learners develop lexical networks over time, specifically in the development of hypernymic networks and word concreteness use (Crossley et al., in press), the development of semantic networks (Crossley et al., 2008), and polysemy knowledge (Schmitt, 1998). While studies that investigate lexical networks and their effects on lexical acquisition have been rare (Meara, 2006), such studies are necessary because they can broaden our knowledge on how deeper level lexical elements contribute to lexical acquisition.

## Neural Network Models

Connectionism is a superordinate term that subsumes a range of network architectures that use parallel processing mechanism. The most common of these are known as artificial neural networks (Broeder & Plunkett, 1994). ANNs are computational algorithms that attempt to mimic cognitive processing. They are thus used to test the validity of cognitive processing models through computer

simulations (Gasser, 1990). ANNs are parallel in order to process simultaneous changes and distributed to learn patterns. The basic theory supporting ANNs is the notion of interconnected units. Two units influence one another via weighted connections. If the product of the output of a unit times the weight of its connection to another unit is positive, it excites the second unit (causes its output to be high); if the product is negative, it inhibits the second unit (causes its output to be low). Most importantly, ANNs can also 'learn.' That is, given an input and a desired output, ANNs can manipulate the values of the weights so that the desired output is attained. When an intermediate level of units is placed between the input and the output units, this learning becomes non-linear because the intermediate level units (called hidden units) allow for back propagation in which their threshold values are able to be adjusted. These types of ANNs are the most common learning networks in connectionist simulations (Broeder & Plunkett, 1994). Such learning networks do not rely on explicit rules. Instead, weights are modified over time to reflect learning history and learned associations (Sokolik & Smith, 1992).

### Neural Networks in Second Language

In the early 1990s there was an interest in demonstrating how ANNs could be applied to classic phenomena common in second language studies. These included studies by Gasser (1990) concerning language transfer and Broeder (1991) concerning pronoun acquisition. Gasser's (1990) ANN findings demonstrated that the learning of an L2 was not as difficult if an L1 had already been learned; however the accuracy of learning in the L2 never reached the accuracy of learning in the L1. Moreover, languages that were similar in word order lead to learning increases. L1 transfer of word order was strongest when the lexicon between the L1 and L2 was most similar. Broeder's (1991) study demonstrated that an ANN could learn Dutch morphemes in an order that corresponded to the acquisition of the same pronouns by Turkish and Moroccan learners. Much later, Meara (2007) used a Boolean network to simulate L2 lexical growth. His study demonstrated that a self-sustaining vocabulary can emerge from simple networks, supporting the notion that the critical process in language learning is the establishment of links between words and the eventual subsumption of these links into a lexical network.

These studies demonstrated the use of neural networks to describe issues of importance to the second language community, but they were not generally followed up in replication studies. However, researchers in bilingualism readily adopted ANN approaches to explain language development in bilingual learners. At issue was whether or not bilingual children depended on a single, distributed lexicon or two (French & Jacquet, 2004), with most theorists favoring the notion of a single lexicon (Li & Farkas, 2002). Research in this area has led to a variety of

neural network models designed to model bilingual cognitive processing. These include the self-organizing model of bilingual processing (SOMBIP; Li & Farkas, 2002) and DevLex (Zhao & Li, 2007).

## Methods

In this study, we want to reduce a complex system to a much simpler one. Thus, while we analyze the potential for an ANN to produce or not produce words in a manner similar to that of beginning L2 students, we do not pretend to present a model that represents all the intricacies and complexities of an entire lexicon. Instead, as suggested by Meara (2006), we intend to build a simple model that removes unnecessary complications under the premise that in emergent systems, simple connections lead to complex structures. However, unlike some simplified versions of complex structures, our model is also theoretically bound and functional in that it explores the properties of words inherent in the conceptual and sense relations of the lexicon and the psycholinguistic properties inherent in the lexicon of the language users.

### Corpora

For this study, we needed to collect a list of frequent words that were produced by beginning L2 learners and a list of frequent words that were not produced by L2 learners but were produced by native speakers of English. Thus we are most interested in looking at active word knowledge, and not just passive word knowledge (Laufer, 1998). We assume that the words in the first list are words that are easier to actively produce and the words in the second list are more difficult to actively produce. We thus needed two corpora (an L2 corpus and an L1 corpus). Because we are interested in natural language use, the corpora needed to be both spoken and unprepared.

The L2 corpus we selected was a corpus of L2 naturalistic speech collect by Salsbury (2000) and used in a variety of studies examining the development of lexical networks in L2 learners (Crossley et al, 2008; Crossley et al., in press). The corpus contains bi-monthly interviews of L2 English learners enrolled in an intensive English program at a large American university. The corpus consists of discussion between L1 interviewers and L2 learners. The interview sessions are characterized by naturally occurring discourse. Learners' proficiency levels were tested upon arrival to the program, and all participants in the study tested into the lowest proficiency level, Level 1, of a 6-level program. The portion of the corpus used for this study focused on six of the learners from various language backgrounds.

A parallel corpus of L1 speech was needed from which to derive the unproduced words. The Santa Barbara corpus (Du Bois, Chafe, Meyer, & Thompson, 2000) was selected because it consists of unprepared speech recordings taken

from people across the United States in naturalistic settings. The variety of the participants in the corpus is sufficient to include different regional origins, ages, gender, and ethnic and social backgrounds. The size of the corpus (about 200,000 words) also allowed for sufficient coverage of frequent English words.

### Word Selection

In this study, we take a simplified approach and argue that words produced by beginning L2 speakers in their first quarter of studying a language are words that are easier to fully acquire (i.e. actively produce). Contrarily, words that were not produced by beginning L2 learners in their first quarter of learning, but were frequent in L1 spoken production were assumed to be more difficult to fully acquire. However, we did not select all produced and unproduced words. Four criteria had to be met for selection. The word had to be produced by at least half of the L2 participants. The word also had to have a frequency above .10 in either the L1 or the L2 corpus respectively. The word's use also had to fit clearly into a noun or verb categorization. If questions arose, the use of the word was analyzed in context to ensure its part of speech category. Lastly, lexical values for the words in all examined categories (polysemy, hypernymy, concreteness, and meaningfulness) needed to be available. For this exploratory study, the first 10 verbs and nouns from each group that fit this criterion were selected. This gave us a word list of 20 nouns (10 produced and 10 unproduced) and 20 verbs (10 produced and 10 unproduced).

### Word Measurements

We selected 4 variables related to L2 lexical networks and L2 lexical acquisition to act as input nodes in our neural network model. These four variables were polysemy, hypernymy, concreteness, and meaningfulness. The first two variables are related to conceptual knowledge. The last two are psycholinguistic measures. All are related to lexical networks. These variables, their links to lexical networks and acquisition, and our methods for computing their values are listed below.

Polysemous words are words that have more than one related sense. Polysemy is related to the *law of least effort*, which states that speakers will economize their vocabulary by extending word senses in order to conserve lexical storage space. Thus, over time, word meanings are extended so that individual words possessed multiple meanings. This is especially true for more frequent words, (Zipf, 1945). Because frequent words have the most senses, learners encounter highly polysemous words most often. From a network perception, words connect not only to a meaning, but also to networks of semantically similar words. In consideration of polysemous words, lexical networks allow learners to recognize meaning relationships between a word's senses (Verspoor & Lowie,

2003) because the word's senses are located within a single lexical item.

Hypernymy is considered a fundamental semantic relationship that is founded on the connection between general and specific lexical items (Haastrup & Henriksen, 2000). Hypernymic relations are hierarchical associations between hypernyms (superordinate words) and hyponyms (subordinate words). Hypernymic relations allow for hierarchical categorizations that define how hyponyms inherit properties from their related hypernyms and allow set inclusion among category members. Hypernymy is consistent with network models in that it allows for the economical representation of lexical properties. Such properties allow for learners to generalize about terms and allow for cognitive economy because every object is part of a conceptual category and not its own conceptual category (Murphy, 2004). For this study, the number of word senses for each selected word along with their hypernymy values were obtained from WordNet (Fellbaum, 1998), which is a lexical reference system inspired by current theories of lexical processing.

Words also differ in their psycholinguistic measurements. For instance, the manner in which words refer to concrete items or abstract concepts is an important distinction. Words that refer to objects, materials, persons or any items that can be seen, heard, felt, smelled, or tasted are more concrete than those that cannot (Toglia & Battig, 1978). More concrete words have advantages for lexical acquisition and long term memory storage over abstract words because concrete words are recalled more quickly, are recognized faster, inform lexical decision tasks to a greater degree, and are pronounced and comprehended more rapidly than abstract words (Paivio, 1991). Meaningfulness refers to a word's capacity to stimulate other associated words. Some words are strongly associated with other words whereas others are weakly associated. If a word is highly associated with other words, it is argued to be more meaningful. Associations such as meaningfulness are important for mediating the organization and memorization of words and afford for easier acquisition (Ellis & Beaton, 1993). To obtain concreteness and meaningfulness scores, we used the Medical Research Council (MRC) psycholinguistic database (Wilson, 1988).

### Analyses

Prior to constructing and training a neural network, simple *t*-tests were conducted to analyze whether significant difference existed between the psycholinguistic and conceptual features of the selected words.

Next, using NevProp, a backpropagation ANN was constructed, with 4 input nodes, 2 hidden nodes, and 1 output node; a bias node with a constant input of 1 was connected to the hidden and output nodes. The ANN was initially trained on the entire data set. This was necessary

Table 1  
*Selected verbs and nouns and word feature scores*

<i>Verb</i>	<i>Poly</i>	<i>Hyper</i>	<i>Concrete</i>	<i>Meaning</i>	<i>Noun</i>	<i>Poly</i>	<i>Hyper</i>	<i>Concrete</i>	<i>Meaning</i>
Think	13	3	342	500	People	6	5	540	612
Speak	5	4	419	508	Time	15	8	343	453
Go	35	1	337	430	Country	5	8	465	472
Know	12	1	274	439	Friend	5	10	450	538
Like	11	2	286	516	Mother	7	15	579	584
Have	20	1	251	331	Man	13	11	618	607
Want	9	1	302	472	Father	9	15	594	554
Work	34	1	402	558	Year	4	7	364	437
Come	22	2	355	408	Child	4	11	582	608
Get	37	1	290	318	University	3	8	533	531
Turn	38	1	359	347	Root	15	7	516	519
Pump	11	5	556	389	Part	18	5	558	443
Point	37	5	464	376	Death	8	8	339	337
Whistle	10	3	579	420	Case	19	7	365	510
Pick	21	3	502	430	Seat	11	8	548	408
Stare	3	2	365	405	Engine	3	10	568	469
Trace	14	2	371	371	Nobody	1	11	586	490
Judge	7	4	506	460	Fire	17	7	595	533
Shoot	22	5	445	457	Reason	9	7	332	393
Pull	24	2	360	410	Figure	18	8	472	513

to capture the relevance of each lexical feature. Later, we tested the accuracy of the ANN on data it had never seen before. Since only 20 examples of verbs and 20 examples of nouns were available, a 10-fold cross validation was performed. For the cross validation, ten pairs of verbs were selected such that one member of each validation pair was a learned verb and one was an unlearned verb; this pair was removed from the training set as reserved for use as the validation set for this trial. For each pair the ANN was assigned a random initial set of weights, was trained on the other 18 verbs, and was tested on the selected pair. This required 10 separate runs of the ANN program.

## Results

*T*-test results for the produced and unproduced verbs showed significant differences in both hypernymy values  $t(1, 18) = -2.61, p < .05$ , and concreteness values  $t(1, 18) = -3.92, p < .001$ , with produced verbs demonstrating lower values in each feature. No other lexical features in the verb group were significant. *T*-test results from produced and unproduced nouns showed significant differences in word meaningfulness,  $t(1, 18) = 2.67, p < .05$ , with produced nouns showing higher meaningfulness values. No other lexical features in the noun group were significant (see Table 2 for details).

A neural net was then trained on the verb data for 500 epochs to enable the net to learn the correct classification. The initial weights of the network were randomly set using

Table 2  
*Means (Standard Deviations) for selected words*

<i>Variables</i>	<i>Produced</i>	<i>Unproduced</i>
Polysemy		
Verb	19.80 (11.80)	18.70 (11.98)
Noun	7.10 (4.04)	11.90 (6.52)
Hypernymy		
Verb	1.70 (1.05)	3.20 (1.47)
Noun	9.80 (3.29)	7.80 (1.69)
Concreteness		
Verb	325.00 (55.22)	450.70 (84.18)
Noun	506.80 (97.08)	487.90 (104.70)
Meaningfulness		
Verb	448.00 (79.02)	406.50 (36.81)
Noun	539.60 (66.09)	461.50 (64.71)

999 as the seed for the random number generator. Results were saved every 50 epochs. The trained network was used to generate a final classification for the 20 training data items. The network classified all verbs correctly. After training on the verbs, NevProp generated a summary of input relevance for the classified verbs. The lexical indices had the following relevance: polysemy = .0005, hypernymy = .0277, concreteness = .8898, meaningfulness = .0819.

The neural net was next trained using the noun data in a similar manner as the verb data. The network classified all nouns correctly. After training on the nouns, NevProp generated a summary of input relevance for the classified verbs. The lexical indices had the following relevance:



polysemy = .1942, hypernymy = .0749, concreteness = .2062, meaningfulness = .5246.

The network was then trained on the verb and the noun set using a 10-fold cross-validation model. The accuracy of the networks on the validation set for the verbs was 95% correct ( $df = 1$ ,  $n = 20$ )  $\chi^2 = 16.36$ ,  $p < .001$ ). The network, when trained on the other 18 verbs, was able to learn each selected pair of verbs except the 9<sup>th</sup> pair. In that case, the trained network correctly classified *Shoot* as unproduced, but mistakenly classified *Come* as unproduced as well. The accuracy of the networks on the validation set for the nouns was 80% correct, ( $df = 1$ ,  $n = 20$ )  $\chi^2 = 7.20$ ,  $p < .01$ ). When trained on the other 18 nouns, the networks were able to learn a significant percentage of their validation nouns. The trained networks misclassified *Man* and *Father* as unproduced and misclassified *Engine* and *Fire* as produced.

## Discussion

This study has demonstrated that an artificial neural network meant to simulate the potential learning mechanisms of second language learners was able to produce and not produce a small selection of nouns and verbs in a similar manner as L2 learners using four features related to lexical network models. Statistical analyses demonstrated that the verb groups (produced and unproduced) differed in concreteness and hypernymy values and this finding was supported by the input relevance found in the training set. This finding provides evidence that the production of verbs might be influenced by concreteness and hypernymy values. Additionally, the noun groups differed significantly in their meaningfulness scores. This was also supported by the input relevance found in the training set. This finding provides evidence that lexical features related to word association might play an important role in L2 noun production.

This study helps support the potential for lexical network models to explain lexical production in L2 learners. Earlier studies (Crossley et al., 2008; Crossley et al., in press; Meara, 2007) have found empirical support for lexical networks in L2 learners. However, these past studies used either Boolean models or computational tools to investigate lexical growth. The studies did not use lexical features related to network models to simulate lexical production and learning. Thus, this study provides a broader perspective on how lexical features can inform lexical production. Also, unlike past ANN models in bilingual studies, this investigation examines which lexical factors influence adult L2 learning. An additional strength of this approach is its simplicity. The model does not depend on multiple associate networks but strictly on one network with variables related to the specific lexical features inherent to the words themselves.

A clear distinction is also made between the learning mechanisms for nouns and verbs. This analysis

demonstrates that ANNs depend on different mechanisms for the learning of nouns as compared to verbs. While dual mechanism models have been posited for regular and irregular verbs, approaches that support different mechanisms for noun and verb acquisition appear rare. This study seems to support the notion that verbs that are less concrete are produced earlier, while nouns that are more meaningful and thus have more associations are produced. One possible explanation for verb production is that concreteness is not an important aspect of verb production. Its absence implies that more abstract verbs are produced first. This finding is also supported by the hypernymy scores. Thus, the verbs produced are not the most ambiguous or concrete, but rather the most abstract. Abstract verbs likely allow L2 learners to overgeneralize their meanings and approximate verbal accuracy with minimal lexical knowledge. Nouns, on the other hand, seem to depend more on meaningfulness than other lexical variables. Thus, the more associations a noun has, the earlier it is produced.

Another important distinction fleshed out in the network model is the relative importance of psycholinguistic features of the lexicon as compared to conceptual features. This study has demonstrated that psycholinguistic features might be more indicative of whether a word is produced than conceptual features such as polysemy and hypernymy. Thus, word production might not be a simple matter of conceptual features contained within the word, but rather based on psycholinguistic judgments of the characteristics of the words. In this manner, words are produced not so much as a result of the inherent conceptual properties of the words themselves, but rather how humans perceive the words.

## Conclusion

Unlike theories of network models where interaction between parallel nodes leads to an unwieldy structure where behaviors are difficult to predict (Meara, 2006), our simple model of lexical production is relatively accessible. In addition, our model is based on computational databases that should likely allow for a scaling up toward natural languages. We also contend that while the network model is simple, it is not limited by generalizations. We do more than just describe words as nodes in a network, but rather give the nodes values taken from both psycholinguistic and lexicographic databases. Thus, although simple, our model accurately represents lexical knowledge within a lexical network.

Because this is an exploratory study, there are of course limitations. In this initial study we have not attempted to control for language transfer between the L2 learners' first and second languages. Previous research has claimed that there is a strong effect for lexico-semantic transfer between languages (Ijaz, 1986). Additionally, we did not use an absolute index of frequency, but rather a proxy

through a polysemy index. Lastly, we were unable to retrieve accurate weights from the 10 fold cross validation. This is the result of each pair of words having a different training set from which to cull the weights. Thus, an overall, systematic analysis of the weights for each individual variable was not possible.

However, we argue that the findings of this study help to support the notion of lexical network models in L2 learners. In addition, these findings provide evidence as to the relative strength of various lexical indices in the production of words by L2 learners. This study provides an important first step in recognizing which properties of words may be important for word production and acquisition in L2 learners.

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