

**The processing of pseudoword form and meaning in production and comprehension:
A computational modeling approach using Linear Discriminative Learning**

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Abstract

Pseudowords have long served as key tools in psycholinguistic investigations of the lexicon. A common assumption underlying the use of pseudowords is that they are devoid of meaning: Comparing words and pseudowords may then shed light on how meaningful linguistic elements are processed differently from meaningless sound strings.

However, pseudowords may in fact carry meaning. On the basis of a computational model of lexical processing, Linear Discriminative Learning (LDL [Baayen et al., 2019](#)), we compute numeric vectors representing the semantics of pseudowords. We demonstrate that quantitative measures gauging the semantic neighborhoods of pseudowords predict reaction times in the Massive Auditory Lexical Decision (MALD) database ([Tucker et al., 2018](#)). We also show that the model successfully predicts the acoustic durations of pseudowords. Importantly, model predictions hinge on the hypothesis that the mechanisms underlying speech production and comprehension interact. Thus, pseudowords emerge as an outstanding tool for gauging the resonance between production and comprehension.

Many pseudowords in the MALD database contain inflectional suffixes. Unlike many contemporary models, LDL captures the semantic commonalities of forms sharing inflectional exponents without using the linguistic construct of morphemes. We discuss methodological and theoretical implications for models of lexical processing and morphological theory. The results of this study, complementing those on real words reported in [Baayen et al. \(2019\)](#), thus provide further evidence for the usefulness of LDL both as a cognitive model of the mental lexicon, and as a tool for generating new quantitative measures that are predictive for human lexical processing.

keywords:

auditory pseudowords, auditory comprehension, speech production, linear discriminative learning, morphology, computational modeling

1 Introduction

Pseudowords such as [blik], i.e. phonologically legal forms that are not in the lexicon of a given language¹, are used extensively in a wide variety of linguistic and psycholinguistic experiments. Typically, the purpose of including such items is to examine how the processing of meaningful words differs from that of strings of sounds or letters that are, by assumption, devoid of meaning. In research on speech perception, for example, pseudowords have been used to study phonological effects, such as phonological neighborhood density and phonotactic probability, on speech processing. [Vitevitch and Luce \(1998\)](#), using a shadowing task, found that while higher probabilities and denser

¹We note that the term “pseudoword” used here is equivalent to and referred to as “nonword” in many published studies.

neighborhoods were associated with longer naming response times for words, correlations became negative for pseudowords. Since pseudowords *ex hypothesi* lack semantics, the phonological effects observed on pseudowords are interpreted to occur at the sublexical level.

But is the processing of pseudowords truly detached from the mental lexicon? What cognitive mechanisms underlie the comprehension and production of pseudowords? Current computational models of lexical processing provide limited insight into this question. In standard interactive activation models of visual (McClelland and Rumelhart, 1981) and auditory word recognition (McClelland and Elman, 1986), for example, there are no entries for pseudowords in the lexicon, reflecting the assumption that pseudowords do not appear in the lexicon and do not carry meaning. Bayesian word recognition models (Norris, 2006; Norris and McQueen, 2008) include mechanisms for modeling the behavior of pseudowords, in order to simulate the situation of encountering unknown words. Although in the latter model pseudowords find their way into the mental lexicon, very little can be said about their semantic make-up or their semantic relations with other words.

Some computational methods provide ways to study the semantics of pseudowords. For example, Marelli et al. (2014) and Amenta et al. (2017) investigate the degree of semantic similarity between a given word and other words that share orthographic or phonological subsequences. The meanings of pseudowords can also be estimated more directly. The triangle model (Harm and Seidenberg, 2004) dynamically computes the meaning of a word from its input codes. Using its networks as trained on words, it can in principle also estimate the meaning of a pseudoword, in the same manner as for a real word, although the amount of activation produced by pseudowords is reported to be substantially less than that produced by words (Harm and Seidenberg, 2004, p. 680–681).

More recently, Baayen et al. (2019) put forward the model of Linear Discriminative Learning (LDL) for the mental lexicon. Just as in the triangle model, meaning is computed dynamically, rather than retrieved. However, the training algorithm behind LDL, detailed below, is much simpler than that of the triangle model. Baayen et al. (2019) show that LDL achieves high accuracy for both word comprehension and production. Furthermore, measures derived from LDL networks are highly predictive of behavioral data.

Cassani et al. (2019) is the first study that used LDL to investigate pseudowords. Taking the 16 pseudowords from the experiment of Fitneva et al. (2009) on children’s lexical categorization, Cassani et al. (2019) generated high-dimensional numeric representations for the semantics of pseudowords (henceforth semantic vectors) and calculated their correlation with the semantic vectors of real words as well as those of morphological functions. They showed that children’s responses could be accurately predicted in this manner.

In this study, we extend the line of pseudoword research to pseudoword auditory recognition, and from there to spoken production: If pseudoword meanings can be computed based on their forms, one can ask to what extent the production of pseudowords can be predicted from their (computed) meanings. Using the pseudoword data from the Massive Auditory Lexical Decision (MALD) database (Tucker et al., 2018), we conducted a large-scale study on auditorily presented pseudowords. As described in detail below, the MALD database comprises a set of recordings of

spoken words and pseudowords, which we used as input for the LDL model to estimate semantic vectors for pseudowords. Moreover, as LDL can model not only comprehension but also production processes, we examined as well the model’s predictions concerning the pronunciation of pseudowords — specifically, their acoustic durations — on the basis of their semantic vectors. Below, we show that measures derived from both comprehension and production networks are all highly predictive of auditory lexical decision times (as a measure of comprehension), as well as of the spoken pseudoword durations (as a measure of speech production). In addition, when compared to the classical form-based measures such as phonological neighborhood density, the LDL measures together provide better prediction accuracy.

A substantial proportion of the pseudowords in the MALD database contains English inflectional suffixes, and hence are morphologically complex. LDL is constructed specifically for being able to process morphologically complex words, including out-of-vocabulary novel complex words. This in turn enables the model to capture in part the inflectional meanings of morphologically complex pseudowords. By way of example, a pseudoword ending in the [ɪŋ] exponent (e.g., [blɪkɪŋ]) is very likely to be interpreted as a certain action with the continuous aspect. In our model, the inflectional meaning of continuous emerges because the [ɪŋ] exponent will be mapped onto an area in semantic space where real words with the [ɪŋ] exponent are located.

The paper proceeds as follows. We begin by describing the architecture of the LDL model (section 2) and the treatment of morphology in current computational models and in LDL (section 3). We then present the methods (section 4) and results (section 5) of modeling the processing of auditory pseudowords with LDL. Finally, we discuss the results against the background of current models of speech production and comprehension, as well as their methodological and theoretical implications for research on lexical processing and morphological theory (section 6).

2 A blueprint of the mental lexicon using Linear Discriminative Learning

The computational model of Linear Discriminative Learning, as laid out in [Baayen et al. \(2019\)](#), makes use of insights from machine learning, but uses implementations that are much simpler and linguistically transparent. The mental lexicon as modeled with LDL comprises five high-dimensional numeric vectors (shown in grey blocks in Figure 1), each of which represents the state of a different subsystem.

1. The **visual vector** is a binary vector that specifies which letter trigrams are instantiated in the visual input. The length of an orthographic cue vector is equal to the number of different letter trigrams in the training data. Trigrams that are present are coded with 1, and those that are absent with 0. The visual vectors for the orthographic words in the training data are brought together as the row vectors of matrix C_o .²

²Previous work has shown that, for form representations, letter trigrams and triphones capture the variability

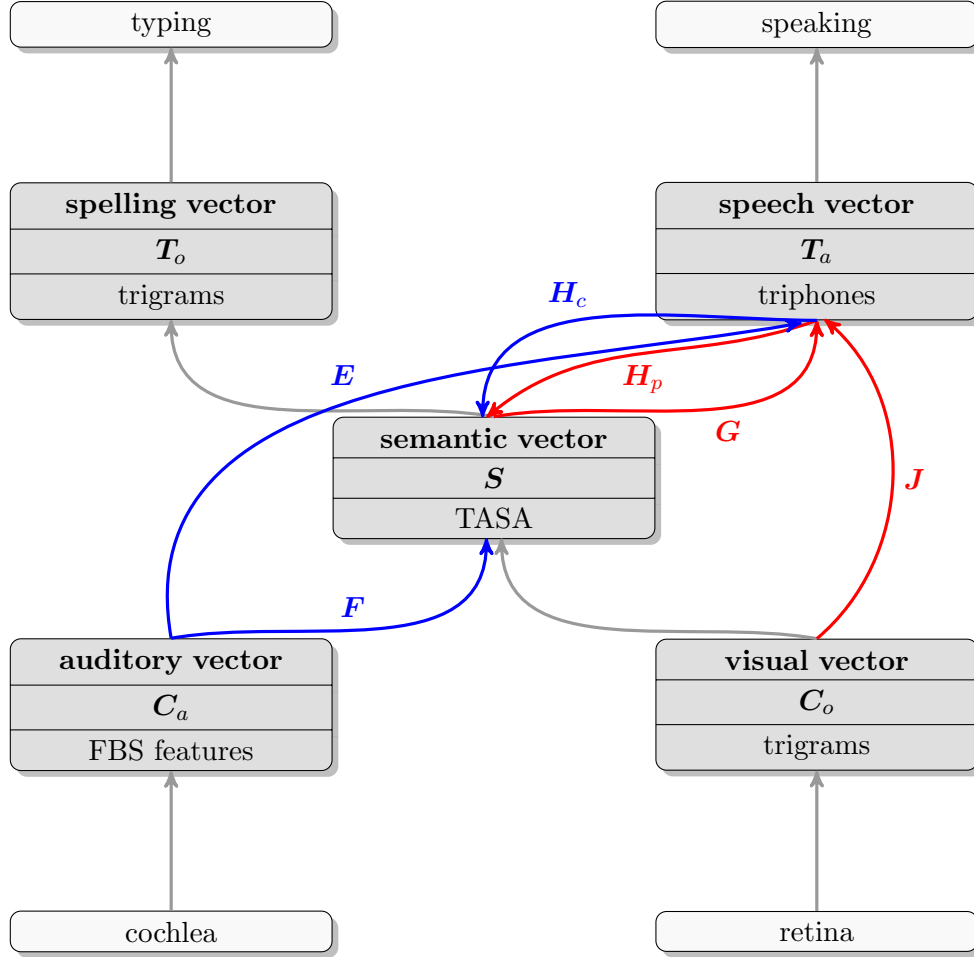


Figure 1: Overview of the discriminative lexicon. Input and output systems are presented in light gray, the vector representations characterizing the state of form and meaning subsystems are shown in dark gray. The vectors of individual words are brought together as the row vectors of the matrices C_o , C_a , S , T_a , and T_o . Arrows represent linear mappings between vectors. Mappings relevant to the present study are labeled. Mappings in red (J , H_p , G) represent networks involved in production, whereas mappings in blue (F , E , H_c) represent networks involved in comprehension. The implementation is detailed in Section 4.2.

2. The **auditory vector** is a binary vector specifying which acoustic features are present in a word’s audio signal. In both Baayen et al. (2019) and the present study, we used the Frequency Band Summary (FBS) features developed by Arnold et al. (2017), which will be described in more detail below (Section 4.2.3). Similar to the visual vector, the length of an auditory cue vector is equal to the number of different FBS features in the training data, and matrix

of neighboring orthographic and phonological information and usually work well not only for English (Milin et al., 2017; Baayen et al., 2019) but also for many typologically different languages such as Latin (Baayen et al., 2018a) and Estonian (Chuang et al., 2019). However, the optimal grain size of form representations can sometimes still be language-dependent. Bigrams, for example, have proven more suitable for Vietnamese due to its more restricted phonotactic constraints (Pham and Baayen, 2015). For modeling with lower-level visual features, see Linke et al. (2017).

C_a has as its row vectors the auditory vectors of words’ speech tokens present in the training data.

3. The **semantic vector** represents a word’s meaning. Semantic vectors, known as embeddings in computational linguistics, can be derived in many different ways from corpora (see, e.g. Landauer and Dumais, 1997; Jones and Mewhort, 2007; Shaoul and Westbury, 2010; Mikolov et al., 2013)³. Following the method outlined in Baayen et al. (2016) and Baayen et al. (2019), we derived semantic vectors from the TASA corpus (Ivens and Koslin, 1991), the corpus that was used by Landauer and Dumais (1997) to construct the semantic vectors of Latent Semantic Analysis. The semantic vectors of the words in the training data constitute the row vectors of matrix S . Details about the method of calculating semantic vectors are provided in Section 3.3, where we explain how we constructed semantic vectors for morphologically complex words.
4. The **speech vector** is a binary vector indicating which triphones should be realized when a word is articulated. Again the length of a speech vector is equal to the number of different triphones in the training data, presence is marked with 1 and absence with 0. The row vectors of matrix T_a are the speech vectors of the words in the training data. In the LDL model, the triphone vectors serve two functions. On the one hand, for production, they represent abstract context-sensitive phonological targets that will further drive articulation⁴. On the other hand, the triphone vectors also play a role in comprehension. (See the discussion of dual-route processing in visual and auditory comprehension in Section 4.2.3.)
5. The **spelling vector** specifies which letter triplets are present in a word that is to be written.

Note that this model does not make use of slot (or position) specific vectors. The visual, spelling, and speech vectors simply consist of indicator variables for the presence of letter or phone triplets. However, by using trigrams or triphones, time information is still implicitly coded in the order sequences. (More details about finding the order of triphones are provided in Section 4.2.2.) As will become clearer later, this implicit time information turns out to be sufficient for obtaining high-quality mappings to and from semantic vectors.

With respect to the mappings between vectors (represented by arrows in Figure 1), here we implemented linear mappings. These are equivalent to networks with input and output units and no hidden layers (and no squashing functions). Effectively, this amounts to a multivariate multiple linear regression approach. These linear mappings can be learned incrementally using the update rule of Widrow and Hoff (1960). For computational convenience, in the present study we estimate mappings using the linear algebra of multivariate regression. Accordingly, each mapping is defined by a matrix A that transforms the row vectors in a matrix X into the row vectors of a matrix Y ; i.e., $Y = XA$. As an example, consider the production network G (cf. Figure 1): We can obtain

³See Melamud et al. (2016) for the pros and cons of different techniques of deriving word embeddings for different NLP tasks.

⁴An ongoing project in our lab is now developing a physical model of the vocal tract that generates speech directly based on articulatory gestural data (Sering et al., 2019). This provides an alternative to triphone representation.

this network by solving $T_a = SG$: $G = S^-T_a$, where S^- is the generalized inverse of S . (We refer the interested reader to Baayen et al. (2019) for an informal introduction to the mathematical details.) Linear mappings are restricted in what they can accomplish, but with carefully chosen input and output representations, they can be surprisingly effective and even solve some non-linearly separable classification tasks (see Milin et al., 2017, for detailed discussion).

3 Models of morphological processing

Roughly half of the words in MALD are inflected. Since the pseudowords are of similar build as the words, roughly half of the pseudowords are potentially inflected variants of a possible but non-existing English word. Therefore, following the lead of Harm and Seidenberg (2004), who discuss in detail how the triangle model performs for inflected words, in the present study we must ensure that our model handles morphologically complex words appropriately. Fortunately, the LDL model, which we use to study the processing of auditory pseudowords, is designed specifically to also produce and understand morphologically complex words. Since the way in which LDL achieves this differs substantially from the way in which standard approaches deal with morphology, in this section we first discuss the theoretical construct of the morpheme in linguistics. We then discuss interactive activation and connectionist computational models of morphological processing. Against this background, we then introduce how LDL handles complex words.

3.1 The theoretical construct of the morpheme

Work on logic (Frege, 1879; Russell, 1905, 1942) has had a profound influence on formal linguistics, leading to the widespread belief that language is grounded in a homomorphism between a calculus (or symbolic algebra) of form units and a calculus based on semantic primitives (e.g. Montague, 1973; Hornstein, 1995). Accordingly, language is viewed as a compositional system, and research is aimed at finding the building blocks of form, the rules for putting these building blocks together, and their semantic correlates.

In linguistic morphology, the field of study that addresses the relation between words' forms and their meanings, the idea that words can be decomposed into morphemes, defined as the smallest units of form that correspond to elementary semantic units, became influential in the middle of the previous century and dominated linguistics in the US in the nineteen forties and fifties. Blevins (2016) refers to this linguistic tradition, which sought to systematize the work of Leonard Bloomfield, as post-Bloomfieldian American structuralism. In this approach, the inflectional variants of the English verb *to walk* — *walks*, *walked*, *walking* — are taken to be composed of the stem *walk* and the morphemes *-s*, *-ed*, and *-ing*, which have as their semantic corollaries THIRD PERSON SINGULAR, PAST, and CONTINUOUS TENSE. For languages with more complex morphology, such as Turkish, a form such as *evlerinizden*, 'from your houses', is analyzed as consisting of a noun stem *ev* (HOUSE), a plural suffix *-ler*, a possessive pronominal suffix *iniz* (YOUR), and a postpositional suffix *den* (FROM). The perspective of generative linguistics on morphology, which builds on

post-Bloomfieldian structuralism, is stated succinctly by Embick and Poeppel (2015): “language comprises a set of representations (e.g. ‘morpheme’) and computations (e.g. ‘concatenation’) whose formal properties are the object of research in (psycho)linguistic theory ...” (p. 357).

The theoretical construct of the morpheme has been extremely influential in psychology and cognitive science, where it is widely believed that morphemes must exist in the mind (Butz and Kutter, 2016; Zwitserlood, 2018). In fact, the majority consensus in current research on morphological processing in the mental lexicon is that morphology is symbolic, localist, decompositional in comprehension, and compositional in production (see, e.g., Smolka et al., 2014; Rastle and Davis, 2008; Beyersmann et al., 2015, 2016; Dell, 1986; Levelt et al., 1999), a tradition that goes back to the seminal work of Forster (1976) and Taft and Forster (1975, 1976).

Yet, already in the fifties, researchers in linguistics started to realize that many languages do not build their words in the simple way suggested by the above example from Turkish (Hockett, 1954). Although the words of just about any language can be analyzed into sequences of morphemes, as beads on a string, and fitted to the procrustean bed of compositionality, this seldom leads to deeper understanding. Many theoretical morphologists therefore regard the morpheme as an infelicitous technical construct (see, e.g., Matthews, 1974; Beard, 1977; Matthews, 1991; Stump, 2001; Blevins, 2006). This line of work in linguistics has led to a series of experimental studies that challenge the primacy of decomposition (in comprehension) and concatenation (in production). These studies call attention to, for instance, the early effects of whole-word properties in both eye-tracking and lexical decision (see, e.g., Baayen et al., 1997; Feldman et al., 2009; Kuperman et al., 2009; Schmidtke et al., 2017), and to phonetic properties of complex words that do not follow from the properties of their constituents (Kemps et al., 2005a,b; Pluymaekers et al., 2005; Kemps et al., 2004).

Several solutions have been put forward for addressing the many fundamental problems associated with the theoretical construct of the morpheme as minimal sign (see, e.g., Blevins, 2016; Chuang et al., 2019, for detailed discussion of the theoretical issues). One solution is to use a variety of formal mechanisms that whip a morphological system into the mold of an item-and-arrangement system such as exemplified by Turkish. An example is the analysis of Hebrew stem allomorphy proposed by McCarthy (1981), according to which the allomorphs *katab* (present) and *ktob* (past) are comprised of two morphemes, a root morpheme consisting of the consonants *ktb* and a vowel morpheme, *a-a* for present and *o* for past tense. For a critique, see Ussishkin (2005).

Another solution is to give up the idea that morphemes are linguistic signs and reconceptualize them as units of form only. Realizational theories of morphology, such as developed by Stump (2001), avoid the term ‘morpheme’ and use the term ‘exponent’ to refer to units of form expressing inflectional or derivational functions. Given a lexical meaning and a set of inflectional features (spelling out number, person, case, tense, etc.), rules and representations are set up that formalize how bundles of inflectional features are realized at the form level. The theory of distributed morphology (Halle and Marantz, 1993) takes inflectional features to be syntactic in nature, and ‘distributes’ these features to different parts of syntactic tree graphs. Unlike realizational theories, distributed morphology retains the term ‘morpheme’, but uses it to alternatively denote units of

form and units of meaning, without positing one-to-one links between the two (Marantz, 2013).

Yet another approach in theoretical morphology, first proposed by Matthews (1974, 1991) and subsequently developed further by Blevins (2003, 2016), is known as Word and Paradigm Morphology. Discarding morphemes and exponents altogether, this approach treats words as basic units for lexical processing. Instead of stringing up small pieces of form into words, the analogical relations within and across paradigms serve as basis for word formation.

3.2 Computational models for morphological processing

In psychology, the two best known computational models for speech production adopted the realizational perspective on morphology. The form part of the morpheme-as-sign and its meaning part are assigned to different representational levels. The models of both Dell (1986) and Levelt et al. (1999) have nodes for concepts and inflectional features, and nodes for morphs. The latter are referred to as morphemes by Dell (1986) and as lexemes in WEAVER. Links between the semantic and form units of morphemes-as-signs have no special status in these models.

Two influential computational models for auditory word recognition, TRACE (McClelland and Elman, 1986) and Shortlist/Shortlist B (Norris, 1994; Norris and McQueen, 2008) do not address morphological processing. TRACE included only monomorphemic words, and the two Shortlist models treat morphologically complex words in exactly the same way as monomorphemic words, including both in a lexical list of target forms for recognition. Similar implementation is found in a more recently developed model, DIANA (Ten Bosch et al., 2015). These models are therefore “full-listing” models, and cannot be expected to perform well for languages such as Turkish or Estonian, for which the probability of encountering out-of-vocabulary inflected forms is simply too high.

Turning to visual word recognition, the interactive activation model (IAM) (McClelland and Rumelhart, 1981) does not address morphologically complex words, and the same holds for the Bayesian reader model of Norris (2006). To our knowledge, the only study that extends the IAM to include the processing of morphologically complex words is the LEIA model proposed by Veríssimo (2018). This model adds a lemma level to the IAM, and partitions nodes at both the word form and lemma levels into two sets: stems on the one hand, and affixes on the other. Form nodes for stems have inhibitory connections between them, and so do the form nodes for affixes. There are no connections between stem forms and affix forms. Affix forms have excitatory connections to their corresponding lemmas (e.g., *ed* to PAST), and vice versa.

The architecture of the LEIA computational model, as well as the architecture of related (but unimplemented) models formulated at higher levels of abstraction such as the stem-based access model of Smolka et al. (2007, 2014), illustrate a problem that becomes substantially exacerbated once languages with more complex morphology than English are considered, namely, that a lot of engineering is required to make the system work properly. Unsurprisingly, morphological theories adopting morphemes or exponents as decompositional units have addressed exactly this question in considerable detail.

What morpheme-based theories, realizational theories, and distributed morphology have in com-

mon is a concern with setting up systems of rules and representations that relate sets of semantic and/or syntactic features to combinations of units of form. The bread and butter of morphological analysis then is to set up these formal systems in the simplest and most insightful way. Such systems typically require extensive use of exception features, and necessitate setting up inflectional classes for subsets of forms that pattern in the same idiosyncratic way. Linguistic morphology has made far more progress here than computational models in psychology. In linguistic morphology, detailed formal methods have been developed that cover a wide range of languages with diverse complex inflectional systems. Localist computational models in psychology, by contrast, have been almost exclusively concerned with English.

However, one area where psychology is far ahead of linguistics is in exploring how learning systems might capture morphological effects without requiring hand-crafting of rule systems and lexicons with exceptions and specialized features for inflectional classes that inform these rules. For comprehension, the triangle model (Seidenberg and McClelland, 1989) in the implementation of Harm and Seidenberg (2004) worked with localist semantic features for English noun plural, past tense, and third person singular inflections. The model learned to predict these features from distributed phonological representations, and presented with inflected pseudowords, the units for these inflectional features were selectively activated. The model successfully learned which semantic functions are realized in words' forms, without having to define exponents for these functions.

Experimentally observed graded effects of form and meaning for derived words have also been explained within the general framework of the triangle model (Seidenberg and Gonnerman, 2000; Plaut and Gonnerman, 2000; Gonnerman et al., 2007), although to our knowledge the model has never actually been used to simulate these effects. Likewise, morphological effects in Hebrew have been discussed from the perspective of distributed connectionist modeling (Velan et al., 2005).

For speech production, the recurrent network developed by Mirković et al. (2005) for Serbo-Croatian noun paradigms implements a realizational model. Localist representations for lemma, number, case, and animacy were implemented in a network that was trained to produce the corresponding inflected phonological forms.

Although the parallel distributed processing (PDP) approach has been successful in calling attention to the importance of learning, the absence of further development and the absence in the literature of successful models for languages with complex inflectional systems suggest that about a decade ago the PDP approach had reached the limits of what it could technically accomplish.

In recent years, neural network technology has rapidly developed far beyond that available to the PDP programme. Artificial neural networks are now widely used in machine learning, and outperform almost all classical symbolic algorithms on tasks as diverse as playing Go (AlphaGo, Silver et al., 2016), speech recognition (deep speech, Hannun et al., 2014), and speech production (WaveNet, Oord et al., 2016). How far current natural language processing technology has moved away from concepts in classical (psycho)linguistics theory is exemplified by Hannun et al. (2014), announcing in their abstract that they "...do not need a phoneme dictionary, nor even the concept of a 'phoneme' " (p. 1).

In the light of these advances in machine learning, several different research strategies suggest themselves. One is to adopt deep learning networks for predicting aspects of human lexical processing. Although prediction accuracy may be expected to be high, deep learning methods tend to be black boxes, in the sense that it is often impossible to understand how exactly they work. Another research strategy is to keep working with the classical linguistic approach to linguistic cognition, using rules and representations. The strategy followed within the LDL research programme strikes a middle ground, and strives to keep the mathematics of the model as transparent as possible while at the same time doing justice to the many insights offered by linguistic theories. However, LDL has in common with the PDP programme that it seeks to minimize the amount of hand-crafting for model building.

3.3 Morphology with LDL

LDL is inspired by Word and Paradigm Morphology (Matthews, 1974; Blevins, 2016), and takes words to be the basic units for lexical processing. Knowledge of morphology is brought into the model through the semantic vectors. Below we provide further detail about how we derive semantic vectors from corpora. Here we first outline the way in which the semantic vectors for morphologically complex words are constructed. As a first step, we define a set of basic semantic units, henceforth lexomes. These lexomes fall into two subgroups, content lexomes on the one hand, and inflectional and derivational lexomes on the other hand. The content lexomes can be morphologically simple forms such as *hand*, but also complex words such as *government* or *handsome*. The inflectional lexomes represent inflectional functions such as number, tense, aspect, person, and voice, and the derivational lexomes function such as agent (*runner*), patient (*addressee*), and negation (*unkind*). Each lexome is paired with a semantic vector. Thus, a lexome can be understood as a pointer to a semantic vector (Milin et al., 2017), but also as a location in a high-dimensional semantic space.

The semantic vector of a monomorphemic word is identical to that of its corresponding lexome. The semantic vector of an inflected word is defined as the sum of the semantic vectors of its associated lexomes. For example, the semantic vector for the noun *walks*, \overrightarrow{walks} , is the sum of the semantic vectors of WALK and PLURAL, i.e., $\overrightarrow{walk} + \overrightarrow{plural}$. By contrast, for the verb *walks*, the semantic vector is given by $\overrightarrow{walk} + \overrightarrow{3sg} + \overrightarrow{present}$.

The semantic vectors that we used in the present study are those described in detail in Baayen et al. (2019). These vectors were constructed from the TASA corpus. The words in this corpus were first parsed into their lexomes. Inflected words were represented by their stem and sense-disambiguated labels for their inflectional functions. By using part of speech tagging (the treetagger of Schmid, 1995), we were able to determine whether a form such as *walks* was used as a verb or as a noun. If it was a verb, its lexomes were WALK, 3SG and PRESENT, but if it was a noun, it was assigned the lexomes WALK and PLURAL. Irregular past tense forms such as *went* were given the lexomes GO and PAST. Derived words, which involve word formation and hence typically have idiosyncratic meanings, were assigned a lexome for the (derived) stem and a lexome for the derivational function. Following Baayen et al. (2016) and Milin et al. (2017), we used Naive Discrimination Learning

(NDL) (Baayen et al., 2011; Sering et al., 2018) to build semantic vectors. The Rescorla-Wagner update rule was applied incrementally to the sentences in the TASA corpus. For each sentence, the algorithm was given the task to predict the lexemes in that sentence from all lexemes present in that sentence. Thus, a given word in a sentence is also predicting itself. After going through all the sentences in the corpus, a $23,562 \times 23,562$ weight matrix \mathbf{A} is obtained. This matrix specifies, for a given lexeme at row i , the association strengths of this lexeme with each of the other lexemes listed in the columns of the weight matrix. We set the main diagonal of the weight matrix to zero, as otherwise the row vectors of the weight matrix, which constitute our semantic vectors, would be dominated by the extent to which words predict themselves (see Baayen et al., 2019, for discussion of the pros and cons — depending on the task — of semantic vectors obtained with or without setting the diagonal of the weight matrix to zero). Furthermore, given that the majority of weights in \mathbf{A} are zeros, indicating no information contained, we further removed columns that have small variances ($\sigma < 3.4 \times 10^{-8}$) in \mathbf{A} . The resulting matrix \mathbf{A} is of dimension $23,562 \times 5,030$. For other ways of bringing in morphology into semantic vector space models, see Luong et al. (2013); Botha and Blunsom (2014); Qiu et al. (2014); Cotterell and Schütze (2015); Chen et al. (2015). The vectors that we used in the present study were constructed without word sense disambiguation. Improved vectors can be obtained when word sense disambiguation and named entity recognition is carried out in addition to a morphological analysis and part of speech tagging, as shown by Long (2018).

In order to ensure that the results reported below are not contingent on the specific way in which we calculated the semantic vectors, or on the TASA corpus, we also conducted the same analyses using word embeddings obtained with Word2Vec applied to a corpus of Tweets. As results are very similar, details are reported in the Appendix, and not further discussed below.

4 Modeling auditory pseudowords

The following two sections present the methods and results of modeling comprehension and production of auditory pseudowords with LDL. Key questions of interest to us fall into three sets. First, how do we evaluate the semantics of pseudowords? For real words, to evaluate model performance, one compares a word’s predicted semantic vector with the semantic vector that served as that word’s gold standard during training. But for pseudowords, there is no gold standard semantic vector to be compared with. One possibility is to inspect the semantic neighborhoods of pseudowords. This helps us locate the position at which a pseudoword lands in the high-dimensional semantic space, as well as which words and how many words the pseudoword is semantically similar to. We then are able to use quantitative measures (e.g., semantic neighborhood density) to predict pseudowords’ acoustic durations and auditory lexicality response times, all of which are provided by MALD.

Second, since the LDL model comprises networks not only for comprehension but also for production, we can ask whether durations and reaction times depend also on how well the pseudoword form that the speaker produced, and that the listeners heard, matches with the form that is pre-

dicted by the pseudoword’s estimated semantic vector. Does it matter how strongly the top form candidate (which typically will not be an existing word) is supported by the pseudoword vector? Do the production and comprehension systems ‘resonate’, such that the correlation of the observed pseudoword semantic vector with the semantic vector predicted by top form candidate is predictive for reaction times and durations?

Third, as mentioned earlier, many pseudowords in the MALD database contain affixes. As morphological effects should emerge from the system even without having to parse pseudowords into pseudostems and real affixes, one would expect the semantic vectors of pseudowords that are generated by the model to be morphologically differentiated. Thus, the semantic vectors of pseudowords with affixes should be different from the semantic vectors of pseudowords without affixes. In addition, finer distinction in affixal meanings should be revealed as well. That is, among pseudowords with affixes, those with the same affixes should be semantically more similar than those with different affixes. Finally, semantic similarity is expected to be observed in relation to words as well. In this regard, the semantic vectors of pseudowords with affixes should also be closer to the semantic vectors of words with corresponding affixes than the semantic vectors of those without. Note that these predictions only apply to inflectional functions, but not to derivational ones, given that LDL makes a strict distinction between inflection and word formation. As a consequence, derived words have their own lexomes, which reflect their own semantic idiosyncrasies (e.g., a worker can denote a specific kind of bee). In this study, we therefore focus specifically on inflection, leaving the study of derived pseudowords to future research.

In the following sections, we first provide further details on the MALD database. We then discuss how the LDL mappings were set up, and introduce the predictors that we derived from the model. We then discuss the results obtained, focusing first on the semantics of inflected pseudowords, and then on the predictions for pseudoword duration and pseudoword reaction time.

4.1 The MALD data

Pseudoword data was obtained from the MALD database (Tucker et al., 2018). This database provides auditory lexical decision responses to 26,793 words and 9,592 pseudowords, collected from 231 monolingual English listeners, aged 17–29. All pseudowords are composed of phonotactically legal syllables. The majority of the pseudowords have fewer than 4 syllables (96%), and no pseudowords have more than 7 syllables. The distribution of the number of syllables in pseudowords is similar to that of the MALD words. The pseudowords of the MALD database were created with the Wuggy generator (Keuleers and Brysbaert, 2010), such that one third of subsyllabic constituents of the input words were exchanged for other phonotactically legal segments with similar transitional probabilities. Thus, if the words from which the pseudowords are derived come with affixes, there is a high probability that pseudowords also inherit affixal forms, for example, [θuznəs], [ɪmbɹɛnsɪn], and [weɪmɪŋ].

All words and pseudowords were recorded by one male native Canadian English speaker. Words were presented in their standard spelling, while pseudowords were presented in their IPA transcrip-

tions. The speaker was experienced and trained in reading the IPA. The speaker pronounced each word once. Pseudowords, on the other hand, were produced with at least three repetitions, and the most fluent rendition was selected for the experiment.

We also made use of pseudoword measures provided by the MALD database. One of the predictors for the analyses of acoustic duration and reaction time was **phonological neighborhood density** (PhonND), defined as the number of words which have an edit distance of one phone (by addition, deletion, or substitution) from a pseudoword. PhonND has been reported to determine pseudoword processing to a substantial extent by previous studies (Vitevitch et al., 1997; Vitevitch and Luce, 1998, 1999).

Another crucial factor that has also been widely studied in the literature is phonotactic probability. Given that this information is not provided by the MALD database, we used the online phonotactic probability calculator developed by Vitevitch and Luce (2004) to obtain the mean **bi-phone phonotactic probability** (BiphProb) for each pseudoword. This measure also serves as one of the predictors for the analysis of duration and reaction time.

4.2 Model definition and predictors derived from the model

This subsection first introduces the mappings (networks) required to obtain pseudoword form vectors from the visual vector of pseudowords’ IPA transcriptions. Subsequently, we introduce the mappings for proceeding from pseudowords’ auditory vectors to pseudowords’ semantics.

4.2.1 Initializing the model with real words

Before we can evaluate the model’s performance on pseudowords, we first have to train the model with the real words. We used the MALD words as the training data. Although MALD contains 26,793 words, we only used 19,412 words for training, as it is only for these words that semantic vectors were found, and hence could be constructed based on matrix **A**. However, many of these words are morphologically ambiguous. For example, the word *walks* can either be the third-person-singular form of the verb *walk*, or the plural form of the noun *walk*. As the semantic vectors of the verb *walks* and the noun *walks* will be different, due to different inflectional vectors being added to the semantic vector of the base word (cf. Section 3.3), the actual number of semantic vectors that we considered was not 19,412, but 23,637. Since in tasks such as single auditory word recognition, no contextual information is available for sense disambiguation, we took all possible meanings of an inflected word into account. For each of the mappings in Figure 1, we obtained the mappings by solving the pertinent equations using the vectors for real words as row vectors of the relevant matrices. In the following subsections, we provide further detail about these mappings and how they were used for generating pseudoword vectors.

4.2.2 From pseudowords' transcriptions to pseudowords' forms

For the speaker in the experiment, the task is similar to a pseudoword naming task. An important difference with standard word naming is that the speaker had to pronounce the pseudowords at least three times. Ignoring this difference, three networks are involved during pseudoword production. In Figure 1, these networks are highlighted in red.

The first network \mathbf{J} maps a visual vector with the IPA trigrams (a row vector of \mathbf{C}_o) to the corresponding speech vector of triphones (a row vector of \mathbf{T}_a). The $23,637 \times 8,601$ matrix \mathbf{C}_o with words' IPA form vectors specifies with 0/1 coding for each of the 23,637 inflectionally distinct (real) words in the MALD which of the 8,601 possible IPA letter triplets it contains. The row vectors of the $23,637 \times 8,601$ matrix \mathbf{T}_a specify which triphones are present in a word. For *walking* [wɔkɪŋ], for example, the triphones are #wɔ, wɔk, ɔkɪ, kɪŋ, and ŋ#, with # indicating word boundaries. Given the one-to-one mapping between IPA trigrams and triphones, the mapping \mathbf{J} , obtained by solving $\mathbf{C}_o \mathbf{J} = \mathbf{T}_a$, is almost completely error-free. Given \mathbf{J} , the estimated speech vectors of pseudowords, the row vectors of $\hat{\mathbf{T}}_a^{(\text{pw})}$, are obtained by multiplication with the $9,592 \times 8,601$ IPA trigram matrix for the pseudowords $\mathbf{C}_o^{(\text{pw})}$:

$$\mathbf{C}_o^{(\text{pw})} \mathbf{J} = \hat{\mathbf{T}}_a^{(\text{pw})}. \quad (1)$$

Although $\hat{\mathbf{T}}_a^{(\text{pw})}$ is a real-valued matrix with the predicted degree of support for each pseudoword's triphones, the correlations of the row vectors of $\hat{\mathbf{T}}_a^{(\text{pw})}$ with the binary, true speech vectors of the pseudowords was 0.98 on average. Given that the triphones that truly exist in each pseudoword are also the most activated ones in $\hat{\mathbf{T}}_a^{(\text{pw})}$, we therefore used the binary triphone speech vector $\mathbf{T}_a^{(\text{pw})}$, instead of the estimated one ($\hat{\mathbf{T}}_a^{(\text{pw})}$) as input for subsequent networks. This procedure is also justified by unclarity as to how exactly to model the selection of the best-sounding pseudoword realization reported in the MALD from the three or more pronunciations that the speaker realized.

The network \mathbf{H}_p takes a speech vector of triphones and maps it onto a semantic vector. The semantic vectors of the words, constructed from the lexome matrix \mathbf{A} as described in Section 3.3, were brought together as the row vectors of a matrix \mathbf{S} of dimension $23,637 \times 5,030$. The mapping \mathbf{H}_p is calculated by solving $\mathbf{T}_a \mathbf{H}_p = \mathbf{S}$ for words. The semantic vectors for the pseudowords (the row vectors of the semantic matrix $\hat{\mathbf{S}}_0$) follow as the product of $\mathbf{T}_a^{(\text{pw})}$ and \mathbf{H}_p :

$$\mathbf{T}_a^{(\text{pw})} \mathbf{H}_p = \hat{\mathbf{S}}_0. \quad (2)$$

When speech production is driven not by visual input, but by internal conceptualization, a semantic vector \mathbf{s} (a row vector of \mathbf{S}) is mapped by the network \mathbf{G} onto a speech vector. The matrix \mathbf{G} is calculated by solving $\mathbf{S} \mathbf{G} = \mathbf{T}_a$ for words. A vector \mathbf{t}_a in \mathbf{T}_a represents the amount of support that triphones receive from the corresponding semantic vector \mathbf{s} in \mathbf{S} ⁵. For pseudowords, we consider the possibility that a predicted semantic vector $\hat{\mathbf{s}}_0$ is mapped by the network \mathbf{G} back

⁵The support from the semantics for the triphones that are quantified in \mathbf{t}_a are very different from measures of phonotactic probability. These phonotactic probability measures are based on co-occurrence patterns in forms, and do not take semantics into account. Thus, mean bigram phonotactic probability is only very weakly correlated with LDL measures, as shown in Table 2.

onto a speech vector $\hat{\mathbf{t}}_0$:

$$\hat{\mathbf{s}}_0 \mathbf{G} = \hat{\mathbf{t}}_0. \quad (3)$$

The predicted pronunciation $\hat{\mathbf{t}}_0$ is of interest as the extent to which it deviates from the actual pronunciation may affect acoustic durations and reaction times. However, by itself, $\hat{\mathbf{t}}_0$ is just a vector of reals that define the degree of support coming from the semantics for each of the triphones known to the model. Typically, only a small minority of triphones receives strong support. In other words, $\hat{\mathbf{t}}_0$ is not an unambiguous representation of a word’s form. Fortunately, triphones contain implicit order information — *abc* and *bcd* can be joined into *abcd* but *pqr* and *qzx* cannot be merged — and hence can be strung together into sequences of phones, i.e., candidates for production, albeit with varying support from the semantics. The **speak** function from the **WpmWithLdl** R package (Baayen et al., 2018b) derives such strings by first placing triphones as vertices in a directed graph, with directed edges connecting mergeable triphones (e.g., *abc* and *bcd*). Words can now be conceptualized as paths in this triphone graph. Algorithms from network science, taken from the **igraph** package for R (Csardi and Nepusz, 2006), are used to enumerate possible paths. To keep computational costs down, before calculating possible paths, the graph is thinned by removing edges with little support from the semantics. The threshold value that we use for removing edges was 0.1, its default value as used in several other studies (Baayen et al., 2019; Chuang et al., 2019; Baayen et al., 2018a). The **speak** algorithm then searches for all possible paths in the graph that start with an initial triphone (*#xx*) and end with a final triphone (*xx#*).

By way of example, for the pseudoword [loks], after removing the triphones (vertices) with little semantic support, the trimmed set contains 101 triphones. Two of them are initial triphones (*#lo*, *#ok*), and four of them are final triphones (*ks#*, *ok#*, *nz#*, *ts#*). The remaining 95 triphones are word-internal triphones (e.g., *iks*, *aks*, *rok*, *oke*, *inz*, *uts*,...). The 101 vertices and legitimate connections between them (edges) are represented as circles and arrows respectively in Figure 2. Although there are often multiple edges between vertices, only three paths are found, as a legitimate pronounceable form needs to begin with an initial triphone (e.g., *#lo*) and end with a final triphone (e.g., *ks#*). These three paths are *#lo*→*lok*→*ok#* (marked in blue), *#ok*→*oks*→*ks#* (marked in red), and *#ok*→*ok#* (marked in purple). For the targeted form [loks] to be detected, the path *#lo*→*lok*→*oks*→*ok#* has to be available. However, the critical edge *lok*→*oks* in this path is not in the graph: it is a novel transition that is absent in the training data of real words. This leaves us with three candidate forms for this pseudoword, which are [lok], [oks], [ok]. For details of this path-searching algorithm for speech production, see Baayen et al. (2018a).

Let \mathcal{P} denote the set of triphone paths returned by the **speak** function for an estimated semantic vector $\hat{\mathbf{s}}_0$. For each path $p \in \mathcal{P}$ there is a corresponding 0/1 triphone vector \mathbf{p} . Each of these triphone vectors is multiplied with \mathbf{H}_p to obtain a corresponding estimated semantic vector $\hat{\mathbf{s}}'_0$:

$$\hat{\mathbf{s}}'_0 = \mathbf{p} \mathbf{H}_p. \quad (4)$$

We refer to the set of vectors $\hat{\mathbf{s}}'_0$ as \mathcal{S} . From this, we derived two measures that, as we shall see

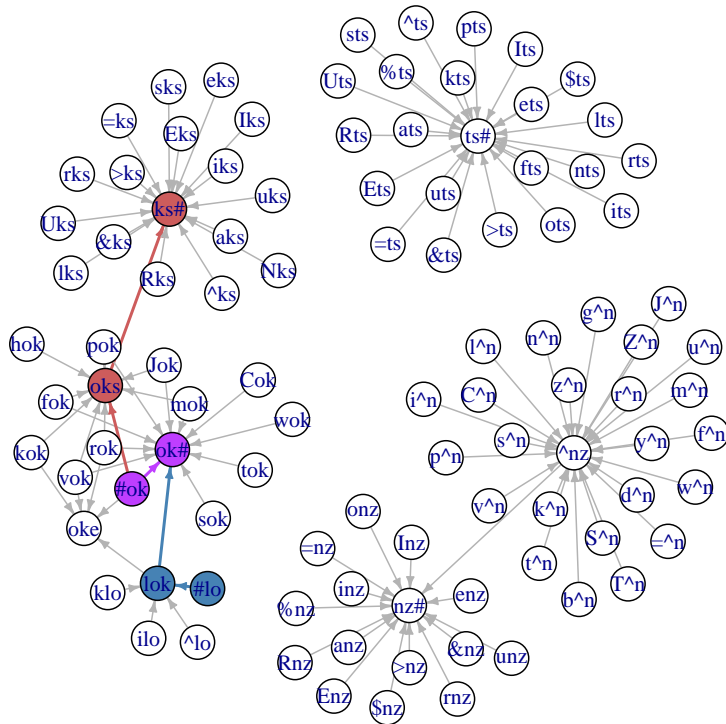


Figure 2: The (thinned) triphone graph highlighting three candidate forms [lok] (blue), [oks] (red), and [ok] (purple) for the target pseudoword [loks].

below, are predictive for both acoustic durations and auditory lexical decision latencies.

- **Average Levenshtein Distance of Candidates (ALDC):** The average Levenshtein distance of all candidate productions from the true pronunciation of a given pseudoword as provided in the MALD. Denoting the form (path) of the pseudoword as produced by the speaker by π , we have that

$$\text{ALDC} = \frac{\sum_i \text{Levenshtein}(p_i \in \mathcal{P}, \pi)}{|\mathcal{P}|}. \quad (5)$$

For the present example, the candidate forms \mathcal{P} for the pseudoword *loks* are *lok*, *oks*, and *ok*, and the Levenshtein distances of each candidate from the pseudoword gold standard pronunciation are 1, 1, 2, respectively. The ALDC is thus 1.33. Note that in cases where no candidate forms are generated by the model, this measure is equal to the number of phones of the pseudoword. Candidate forms such as *lok*, *oks*, and *ok* are conceptually similar to the phonological neighbors of standard production models, and the ALDC measure is therefore conceptually similar to classical measures of phonological neighborhood density. Larger ALDC values indicate that the candidate forms are very different from the intended pronunciation.

indicating a sparse form neighborhood. In the general discussion, we return to the question of how these neighborhood effects can be understood within our theoretical framework, as in this framework exemplars do not exist independently — all they do is leave traces in the mappings.

- **Semantic Correlation of Predicted Production (SCPP):** The maximum of the correlations between the semantic vector \hat{s}_0 predicted from the speech vector and any of the semantic vectors $\hat{s}'_0 \in \mathcal{S}$ generated from the candidate forms:

$$\text{SCPP} = \underset{i}{\operatorname{argmax}} r(\hat{s}_0, \hat{s}'_{0_i} \in \mathcal{S}). \quad (6)$$

For the pseudoword [loks], the correlations of its semantic vector with the candidate forms are 0.64 for [lok], 0.47 for [oks], and 0.01 for [ok]. The SCPP is hence the correlation between the semantic vectors of [loks] and [lok]. When no predicted forms are generated by the model, this measure will be 0. The SCPP is higher when the semantics of the generated form better approximate the generated meaning⁶.

4.2.3 From pseudowords’ audio files to pseudowords’ semantics

Thus far, we have focused on the speaker. We now consider the modeling of how listeners understand pseudowords. For modeling auditory comprehension, we need form vectors that specify key properties of the audio signal. These form vectors are brought together in the matrices \mathbf{C}_a for words and $\mathbf{C}_a^{(\text{pw})}$ for pseudowords. As acoustic features we made use of the Frequency Band Summary (FBS) features developed by Arnold et al. (2017). FBS features are summaries of the spectral information embedded in the speech signal. A word is first divided into chunks at the positions of the minima of the Hilbert-transformed envelope of the waveform. Within each chunk, consecutive power spectra of 5 ms windows are taken and then mapped onto 21 frequency bands on the MEL-frequency scale. Intensities in these frequency bands are subsequently discretized into 5 levels, and the distribution of the intensities in a band are then summarized in a FBS feature which brings together the initial and final intensity, maximum and minimum intensity, and median intensity. By way of example, the feature `band1-start1-median2-min1-max4-end2-part1` specifies that for the first frequency band (`band1`) of the first chunk of the word (`part1`), the intensity of the initial window is 1 (`start1`), that of the final window is 2 (`end2`), and that the median, minimum, and maximum intensities are 2, 1, and 4 (`median2`, `min1`, `max4`) respectively. We extracted the FBS features from the audio files of the MALD database with the `AcousticNDLCodeR` package (Arnold, 2017). The total number of different FBS features extracted for the MALD words was 26,336. The $23,637 \times 26,336$ auditory matrix \mathbf{C}_a defines for each word (rows) which FBS features (columns) are present. Since each form vector in \mathbf{C}_a has a corresponding semantic vector in \mathbf{S} , we can again use a straightforward linear

⁶We also calculated the average semantic correlation between all predicted forms and the target form. It is a measure very similar to SCPP ($r = 0.81$), and its effect on duration and reaction time is virtually indistinguishable from that of SCPP, and is therefore not discussed further.

mapping to project acoustic vectors into semantic space (the \mathbf{F} mapping in Figure 1). The mapping \mathbf{F} is obtained by solving $\mathbf{C}_a \mathbf{F} = \mathbf{S}$ for words. Let the $9,592 \times 26,336$ matrix $\mathbf{C}_a^{(\text{pw})}$ contain as its row vectors the indicators for the FBS features of the 9,592 pseudowords⁷. The semantic vectors estimated for pseudowords are summarized by a $9,592 \times 5,030$ matrix $\hat{\mathbf{S}}_1$:

$$\mathbf{C}_a^{(\text{pw})} \mathbf{F} = \hat{\mathbf{S}}_1. \quad (7)$$

For visual word recognition, Baayen et al. (2019) found that a dual-route setup, with a direct route straight from orthographic vectors to semantic vectors, and an indirect route going from orthographic vectors to triphone vectors and from the triphone vectors to the semantic vectors, afforded greater precision (see Wong and Chen, 1999; Perrone-Bertolotti et al., 2012; Newman et al., 2012; Jared et al., 2016; Bitan et al., 2017; Jared and O'Donnell, 2017; Amenta et al., 2017, for detailed discussion of dual routes in reading). This result led us to inquire whether a second, indirect route, would also enhance model performance for auditory comprehension. We designed this second route as follows: first, the acoustic cue vector in \mathbf{C}_a is mapped onto its corresponding triphone vector in \mathbf{T}_a . Subsequently this vector in \mathbf{T}_a is mapped onto a semantic vector in \mathbf{S} . The two mappings required for this indirect route are given by the matrices \mathbf{E} and \mathbf{H}_c in Figure 1. The mappings \mathbf{E} and \mathbf{H}_c are obtained by solving $\mathbf{C}_a \mathbf{E} = \mathbf{T}_a$ and $\mathbf{T}_a \mathbf{H}_c = \mathbf{S}$. Given these mappings for words, the semantic vectors $\hat{\mathbf{S}}_2$ predicted for pseudowords by the indirect route are calculated as follows:

$$\mathbf{C}_a^{(\text{pw})} \mathbf{E} \mathbf{H}_c = \hat{\mathbf{S}}_2. \quad (8)$$

In what follows, we use the notation $\hat{\mathbf{s}}_1$ for a row vector of $\hat{\mathbf{S}}_1$ (direct route) and $\hat{\mathbf{s}}_2$ for a row vector of $\hat{\mathbf{S}}_2$ (indirect route).

From this comprehension model, we derived further measures to quantify semantic relations between pseudowords and real words. To gauge semantic similarity, traditionally it is common to work with the angle between the semantic vectors of words, using either the cosine similarity or correlation measure. In addition to angle measures, the relation between two semantic vectors can be gauged by their proximity as well. For the semantic vectors that we used, which are not normalized for length, a measure of proximity, such as the Euclidian distance, is potentially informative. To illustrate this, the left panel of Figure 3 presents three semantic neighbors of the word *chocolate*, whose semantic vectors are either highly correlated with the semantic vector of *chocolate* (i.e., small angles) or in its vicinity (i.e., short distance). These three word neighbors are *chocolates*, *candy*, and *vanilla*. The angles between each of their semantic vectors and the semantic vector of *chocolate* are denoted by α_1 , α_2 , α_3 , and the Euclidean Distances from each of them to *chocolate* are denoted by d_1 , d_2 , and d_3 respectively. As can be seen, the plural form *chocolates* is semantically closest to

⁷Given the high variability of natural speech, it is very likely that there will be some novel FBS features in speech tokens of previously encountered words, in newly encountered out-of-vocabulary morphologically complex words, and for pseudowords. Nevertheless, for the present data, no less than 73% of the pseudowords have all their FBS features present. It is only for 2.3% of the pseudowords that more than five FBS features are missing in $\mathbf{C}_a^{(\text{pw})}$. Since missing FBS features have zero weights, they have no influence on the predictions.

chocolate, given that both α_1 and d_1 are the smallest among the three. Interestingly, the remaining two words, *candy* and *vanilla*, are closely related to *chocolate* in different ways. While *candy* has a smaller angle with *chocolate* than *vanilla* does ($\alpha_2 < \alpha_3$), *vanilla* is however closer to *chocolate* in distance than *candy* ($d_2 > d_3$). In fact, it seems that the angle and distance measures have brought together different groups of semantic neighbors. For *chocolate*, according to the the angle measure, its most correlated words are *chocolates*, *candy*, *cookie*, *butter*, *cream*, and *cake*. According to the distance measure, words that are nearest to *chocolate* are *chocolates*, *vanilla*, *frosting*, *peppermint*, *lemonade*, and *muffin*. Except that the plural form *chocolates* is listed as top in both measures, it appears that the two measures are capturing different semantic relations. Exactly what semantic relations are gauged by angle and distance measures as applied to the present semantic vectors is beyond the scope of this study. In what follows we will see that both angle-based and distance-based measures are informative about the lexical processing of the pseudowords.

An issue deserving further scrutiny is how the semantic predictions generated by the direct and the indirect routes differ. For the MALD words, the correlations of the semantic vectors generated by the two routes are generally high ($\bar{r} = 0.73$). Upon closer inspection, when the two-route correlation is low, it usually can be traced to the phonological aspect of the indirect route having been foregrounded. The right panel of Figure 3 plots the distributions of the correlations between the word *street* and all the other words in the training data, by means of the corresponding estimated probability density functions. The blue line indicates the correlations calculated between the semantic vector generated by the direct route and the (gold standard) semantic vectors of all the other words, whereas the red line indicates the correlations calculated with the semantic vector generated by the indirect route. The correlation between the semantic vectors derived from the two routes is 0.39, but the density curve for the direct route is shifted to the left compared to the curve of the indirect route ($p < .00001$, two-sample Kolmogorov-Smirnov test).

For the direct route, the most correlated semantic neighbor is *streets*, followed by *alley*, *lane*, *road*, and *avenue*. As to the indirect route, among the most correlated words we find *treat*, *treats*, *treated*, *streets* and *greet*. Since the second half of the indirect route maps high-level phonological representations (T_a) to semantics S , in this case the predicted semantics is influenced more by words' canonical phonological forms. Given that the two routes predicted exactly the same semantic vectors for 4.5% of the MALD words ($r = 1$), and given that half of the words have a two-route correlation over 0.8, it is clear that the effect of canonical phonological forms is not across-the-board. Nevertheless, because the indirect route is forced through a layer of more abstract phonological triphones, the emergence of semantic neighbors that are more similar in their phonological form is to be expected.

In total four measures were derived from the comprehension networks. These include a distance measure (EDNN), an angle measure (NNC), a density measure (ALC), and a two-route measure (DRC). Except for the last measure, we calculated all measures for both the semantic vectors derived from the direct route (\hat{s}_1) and for those derived from the indirect route (\hat{s}_2). In what follows we present the formal definitions only for the direct route. Those for the indirect route can be obtained by

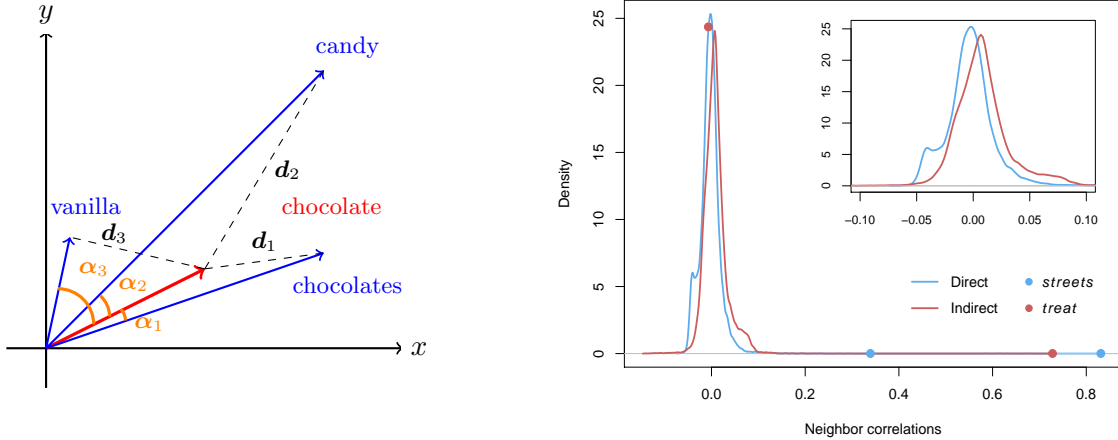


Figure 3: Left panel: graphical illustration of angles and distances for the semantic neighbors of *chocolate*; right panel: estimated probability density functions for the correlations of *street* with other words for the direct route (in blue) and the indirect route (in red). The smaller inset plot shows the same densities restricted to correlations ranging between -0.1 and 0.1, to highlight the difference between the two densities. The dots on the density curves indicate the correlations of *street*’s two semantic vectors with the semantic vectors of *streets* and *treat*, the closest neighbors for the direct and the indirect routes. The blue dot at correlation 0.34 denotes the correlation of *street* and *streets* according to the indirect route.

substituting \hat{s}_2 for \hat{s}_1 .

- **Euclidean Distance from Nearest Neighbor (EDNN):** The Euclidean distance from the semantic vector \hat{s}_1 produced by the direct route to its closest semantic word neighbor:

$$\text{EDNN} = \underset{i}{\operatorname{argmin}} \operatorname{dist}(\hat{s}_1, s_i). \quad (9)$$

Distances were calculated using the FNN package of R (Beygelzimer et al., 2018).

- **Nearest Neighbor Correlation (NNC):** The maximum of the correlations between a pseudoword’s estimated semantic vector and words’ semantic vectors:

$$\text{NNC} = \underset{i}{\operatorname{argmax}} r(\hat{s}_1, s_i). \quad (10)$$

We used the Pearson correlation rather than the cosine similarity. As the two are strongly correlated ($r = 0.99$), and as the correlation measure is the cosine of the angle of centered vectors, the two measures can be interchanged without affecting the results. The NNC is high when the angle between the two vectors is small and the pseudoword’s meaning is similar to that of a real word.

- **Average Lexical Correlation (ALC):** The mean of the correlations of a pseudoword’s es-

estimated semantic vector with each of the words’ semantic vectors. Denoting the number of different word tokens by v , we have:

$$\text{ALC} = \frac{\sum_{i=1}^v r(\hat{s}_1, s_i)}{v}. \quad (11)$$

Higher values of ALC indicate that a pseudoword vector has “landed” in a denser semantic neighborhood.

- **Dual Route Consistency (DRC):** The correlation between the semantic vector estimated from the direct route and that from the indirect route :

$$\text{DRC} = r(\hat{s}_1, \hat{s}_2). \quad (12)$$

When the DRC is higher, the semantic vectors produced by the two routes are more similar to each other.

Figure 4 provides an illustration of how these measures are calculated. The left panel shows the semantic vectors of a pseudoword (\hat{s}_1) and three real words (s_{w1} , s_{w2} , s_{w3}). Given that the pseudoword is the closest to s_{w2} in distance, for this pseudoword $\text{EDNN} = d_2$. With respect to the angles, let $f(\alpha)$ denote the cosine of the angle or the correlation between the two vectors. Then $\text{ALC} = (f(\alpha_1) + f(\alpha_2) + f(\alpha_3))/3$, and as \hat{s}_1 and s_{w1} have the smallest angle, $\text{NNC} = f(\alpha_1)$. Finally for DRC (right panel), as it is the measure of the angle between the semantic vectors estimated via the two routes, $\text{DRC} = f(\alpha_{pw})$ in this case.

It is worth noting that morphological information is embedded in the semantic vectors of words (cf. Section 3.3). When the semantic vectors for pseudowords are generated (via Equations 7 and 8 for the direct and indirect route respectively), the predicted morphological information for pseudowords will be in their semantic vectors as well, without the necessity of doing any morphological parsing. The reason for this is that the mappings from form to meaning as established for real words are sensitive to morphology, albeit indirectly. Through the same mappings, an auditory pseudoword ending in [ŋ], for instance, will be mapped onto a general area of semantic space where real words with the [ŋ] exponent are located. Thus, when the measures described above are calculated, morphological information of words and pseudowords will be both taken into account.

5 Results

For the analyses, we included only pseudowords with correct responses in MALD (i.e., those pseudowords that were rejected as words). Nineteen pseudowords were excluded because they received unanimous “word” responses. This left us with 9,573 pseudowords. In what follows, we first examine the effect of inflectional affixes in pseudowords on their semantics. This analysis clarifies the consequences of morphological complexity according to our model. The next two sections report the structure on pseudoword duration and response time. We are interested in the extent to which the

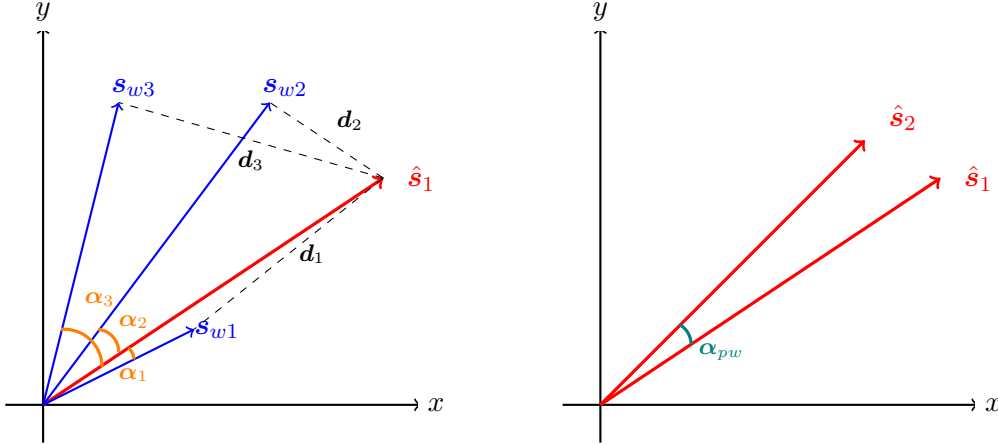


Figure 4: A pseudoword’s estimated semantic vector derived from the direct route (\hat{s}_1) and the semantic vectors of three word neighbors (s_{w1} , s_{w2} , s_{w3}) are shown in the left panel. The distances between the pseudoword from the three words are d_1 , d_2 , and d_3 respectively, and the angles are indicated by α_1 , α_2 , and α_3 . The right panel shows the estimated semantic vectors derived from the direct route (\hat{s}_1) and the indirect route (\hat{s}_2), and the angle α_{pw} between them.

measures derived from the model can account for pseudoword production and perception, and how their predictability is when compared to some classical form-based measures such as neighborhood density and biphone phonotactic probability.

5.1 Pseudoword morphology

As mentioned above, the pseudowords in MALD are created based on real words. If the base real word is an inflected word, then the corresponding pseudoword is very likely to carry the inflectional exponent as well. However, since the base real words are not available to us, we therefore labeled the inflectional functions of the pseudowords according to their forms by ourselves, using a combination of scripting and hand-correction. For example, the pseudoword /sprikɪŋ/ looks like a verb with the inflection of continuous aspect, and [frɪnist] is reminiscent of an adjective in its superlative form⁸. In total, seven inflectional functions were identified (following Baayen et al., 2019): COMPARATIVE, SUPERLATIVE, CONTINUOUS, PAST, PERFECTIVE, PERSON3, and PLURAL. However, due to form similarity and the lack of contextual information, PAST and PERFECTIVE cannot be distinguished from each other. The same happens for PERSON3 and PLURAL, as there is no way to tell which inflectional function a pseudoword has solely based on its inflected form. We therefore combined the ambiguous inflectional functions and partitioned the inflected pseudowords into five sets, the distribution of which is shown in Table 1. It turns out that nearly half of the pseudowords end in what could be an inflectional exponent of English. Note that the 110 pseudowords with the SUPERLATIVE form could possibly also be analyzed as realizing PAST/PERFECTIVE (e.g., [æpɪst] as an inflected variant of the verb [æpɪs]). These 110 pseudowords are thus included in both the

⁸Given that the labeling is only based on suffixes, we acknowledge the limitation of not taking irregular forms into consideration.

Table 1: The distribution of inflected pseudowords in MALD.

	# of pseudowords
COMPARATIVE	481
SUPERLATIVE	110
CONTINUOUS	722
PAST/PERFECTIVE	1015
PERSON3/PLURAL	1773
Uninflected	5581

SUPERLATIVE and the PAST/PERFECTIVE sets.

Even though the inflectional functions were not specified explicitly by means of form units when the semantic vectors of pseudowords were estimated, we expected that pseudowords labeled with the same inflectional function should be semantically similar to each other, and meanwhile semantically distinct from those labeled with different functions or uninflected pseudowords.

To gauge semantic similarities between inflected and uninflected pseudowords, we calculated, for each pseudoword, its correlations with all the other pseudowords⁹. Figure 5 presents boxplots, for each of the five inflectional categories that we distinguish, that visualize the distributions of correlations for three subsets of pseudowords: pseudowords belonging to the same inflectional category (Same), pseudowords belonging to a different inflectional category (Different), and pseudowords that are uninflected (Uninflected). Within each panel, two p -values are listed, the first referring to the Same and Different subsets, and the second to the Same and Uninflected subsets. These p -values are taken from regression models in which the Same subgroup is the reference level of a factor **type** (using treatment coding), and pertain to standard t-tests evaluating the presence of significant differences with the reference level.

As can be seen, significant contrasts are detected for pseudowords with the inflectional functions of COMPARATIVE, CONTINUOUS, and PERSON3/PLURAL, with respect to both Different and Uninflected subsets. The absence of differentiation for the SUPERLATIVE is likely due to the small number of superlative forms (110): although the superlative forms are technically ambiguous, it seems to us that a form such as [æpɪst] is most plausibly a superlative. The PAST/PERFECTIVE forms are systematically ambiguous, and hence the absence of semantic clustering is perhaps unsurprising. The emergence of some clustering for PERSON3/PLURAL might be due to the shared underlying dimension of number: singular for verbs and plural for nouns. Possibly the semantic vectors have picked up this commonality with respect to number.

We further expected that the same inflectional relation should be visible not only within pseudo-

⁹These correlations are necessarily small. The semantic vectors of morphologically complex pseudowords can be conceptualized as the sum of two vectors, namely the vector of the inflectional function \mathbf{i} and that of the pseudoword stem \mathbf{k} . When comparing the semantic similarity of two complex pseudowords with the same exponent, the pseudoword semantic vectors (\mathbf{p}_1 and \mathbf{p}_2) can be seen as noisy versions of the semantic vector \mathbf{i} : $\mathbf{p}_1 = \mathbf{i} + \mathbf{k}_1$, $\mathbf{p}_2 = \mathbf{i} + \mathbf{k}_2$. As \mathbf{k}_1 and \mathbf{k}_2 will tend to be much more orthogonal than is the case for real words, the semantic similarity between \mathbf{p}_1 and \mathbf{p}_2 is inevitably very low. The low correlations between pseudowords are consistent with the low activations reported by Harm and Seidenberg (2004) in their simulation study of pseudoword inflection.

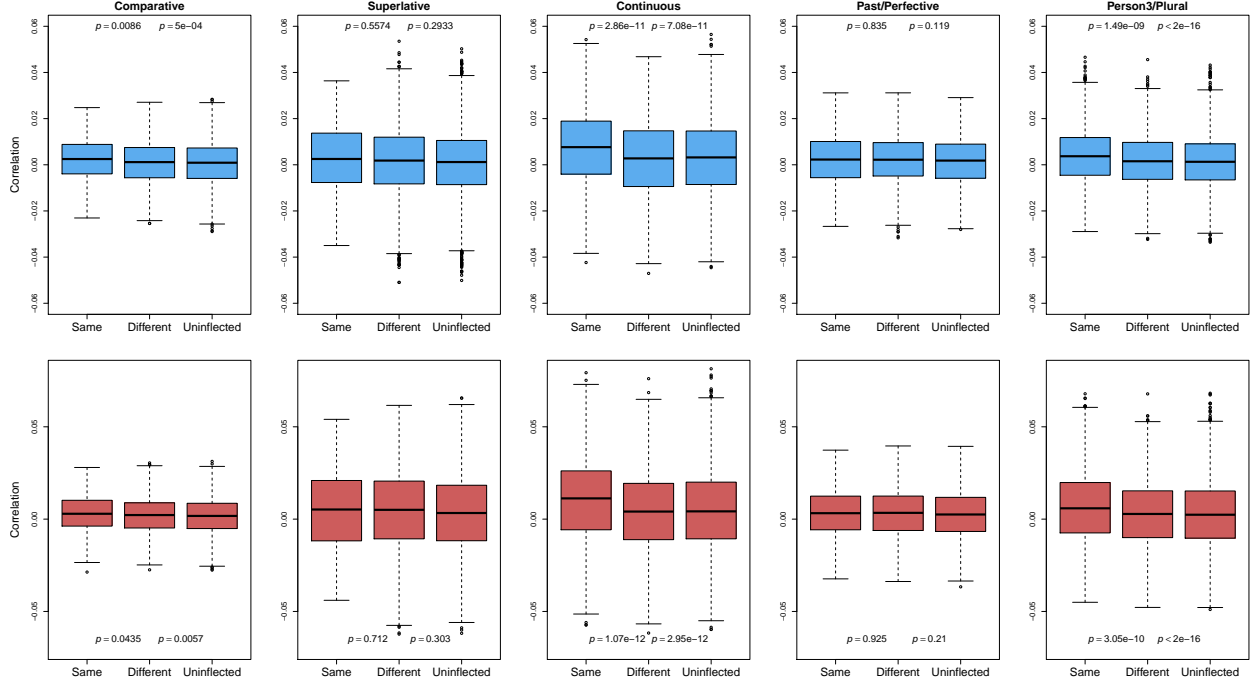


Figure 5: Boxplots of inflected pseudowords’ correlations with other pseudowords of the same, and of different inflectional categories, and with uninflected pseudowords. The upper panel presents the correlations calculated based on the direct route, and the lower panel presents those calculated based on the indirect route. The p -values in the graphs are taken from regression models in which correlations are predicted by different inflectional categories. The first p -value is for the comparison between Same and Different categories, and the second one is for that between Same and Uninflected categories.

words, but between pseudowords and real words as well. Thus, inflected pseudowords would be closer to words with the corresponding inflectional functions. The boxplots in Figure 6 present the distributions of inflected pseudowords’ correlations with inflected and uninflected real words. The pattern of higher semantic similarity between pseudowords and words of the same inflectional functions is clearly seen in CONTINUOUS, PAST/PERFECTIVE and PERSON3/PLURAL (the third to fifth columns). For COMPARATIVE and SUPERLATIVE, higher correlations within the same inflectional categories were however not observed (the first and second columns). The small number of comparatives and superlatives in the dataset of real words (113 and 95 out of 12,175 inflected words), hence reflecting a lack of power, could be the reason for the absence of clear difference here. Taken together, the present results demonstrate that the semantics of inflectional functions do emerge to some extent for the pseudowords, provided that the pertinent inflectional functions are well enough attested in the training and test data.

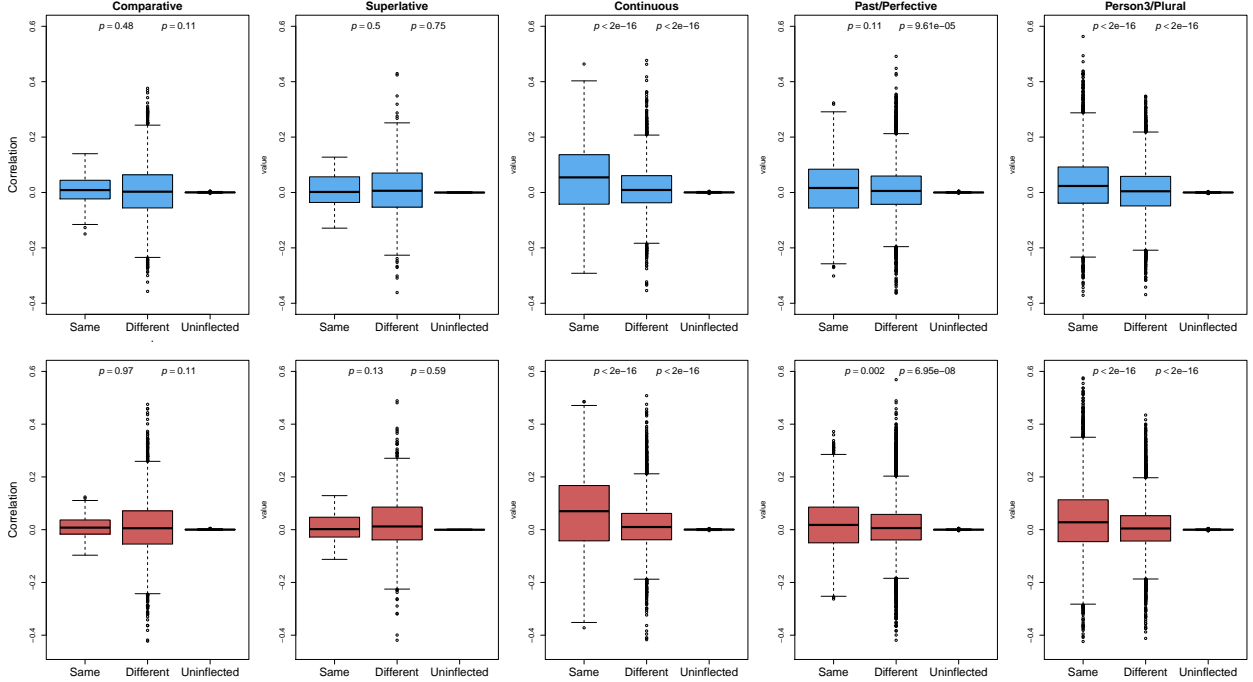


Figure 6: Boxplots of inflected pseudowords’ correlations with real words of the same, different inflectional categories, and with uninflected words. The upper panel presents the correlations calculated based on the direct route, and the lower panel presents those calculated based on the indirect route. The p values in the graphs are taken from regression models in which correlations are predicted by different inflectional categories. The first p value is for the comparison between Same and Different categories, and the second one is for that between Same and Uninflected categories.

5.2 Pseudoword duration

Predictors with skewed distributions were transformed¹⁰. The distributions of the transformed predictors are presented in Figure 7. The pairwise correlations between all the predictors are presented in Table 2. We note that for all the predictors, pseudowords significantly differ from words, according to two-sample Wilcoxon tests (for all predictors, $p < 0.00001$). In general, the LDL measures show that pseudowords are less “word-like”. Pseudowords tend to be more distant from the nearest word neighbor (larger **EDNN**), they tend to have larger angles with the nearest word neighbor (smaller **NNC**), they are located in a sparser semantic neighborhood (smaller **ALC**), their predicted pronunciations tend to deviate more from the targeted pronunciations, resulting in larger **ALDC** and smaller **SCPP**¹¹.

We first fitted a Generalized Additive Model (GAM) to square-root transformed pseudoword

¹⁰PhonND, EDNN, and NNC were log-transformed. We took the square root of BiphProb, the cube of DRC, and the square of SCPP. The choice of transformation is motivated solely by the necessity to reduce outlier structure and stabilize subsequent regression modeling. Note that the distribution of PhonND is still very skewed after log transformation. This is because 63% of the MALD pseudowords has 0 phonological neighbors.

¹¹Comparisons of means between words and pseudowords, as well as the density plots of these measures for words, are provided in supplementary materials. For comparisons based on other phonological measures, see Tucker et al. (2018).

Table 2: Pairwise Pearson correlations between predictors. Subscripts 1 and 2 indicate measures derived from the direct and indirect route respectively. Absolute correlations between different predictors greater than 0.4 are highlighted in bold.

	PhonND	BiphProb	EDNN ₁	NNC ₁	ALC ₁	EDNN ₂	NNC ₂	ALC ₂	DRC	ALDC	SCPP
PhonND	1	-0.13	-0.41	0.21	0.11	-0.41	0.20	0.14	0.14	-0.62	0.10
BiphProb	-0.13	1	0.11	-0.05	-0.01	0.11	-0.03	-0.02	-0.04	0.11	0.15
EDNN ₁	-0.41	0.11	1	-0.45	-0.28	1	-0.46	-0.33	-0.33	0.42	0.00
NNC ₁	0.21	-0.05	-0.45	1	0.57	-0.45	0.62	0.49	0.33	-0.18	0.01
ALC ₁	0.11	-0.01	-0.28	0.57	1	-0.28	0.54	0.87	0.19	-0.09	0.01
EDNN ₂	-0.41	0.11	1	-0.45	-0.28	1	-0.46	-0.33	-0.32	0.42	0.00
NNC ₂	0.20	-0.03	-0.46	0.62	0.54	-0.46	1	0.68	0.38	-0.17	0.00
ALC ₂	0.14	-0.02	-0.33	0.49	0.87	-0.33	0.68	1	0.21	-0.11	0.01
DRC	0.14	-0.04	-0.33	0.33	0.19	-0.32	0.38	0.21	1	-0.13	-0.01
ALDC	-0.62	0.11	0.42	-0.18	-0.09	0.42	-0.17	-0.11	-0.13	1	-0.38
SCPP	0.10	0.15	0.00	0.01	0.01	0.00	0.00	0.01	-0.01	-0.38	1

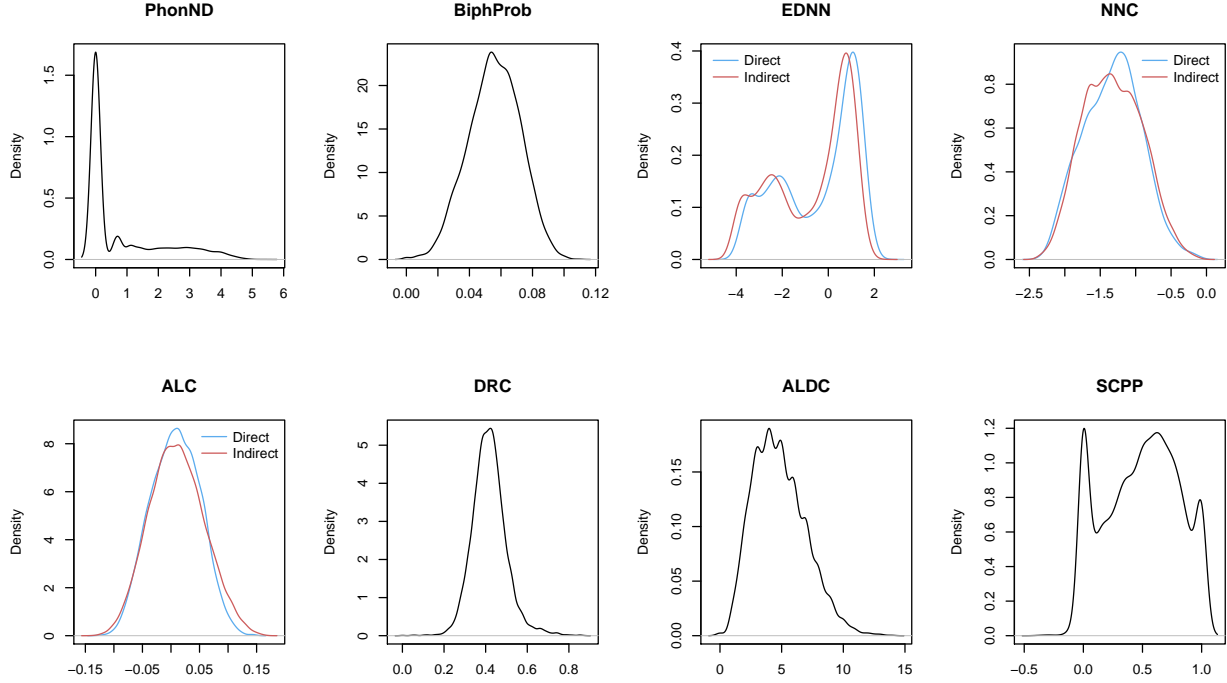


Figure 7: The density plots of transformed predictors in the present study. For EDNN, NNC, and ALC, which can be derived from the direct and indirect routes, two distributions are plotted.

duration with as predictors **PhonND** and **BiphProb**, the two phonological form measures that have been the focus of previous pseudoword studies (cf. Vitevitch et al., 1997; Vitevitch and Luce, 1999). Given the semantic difference between inflected and uninflected pseudowords (Section 5.1), a binary variable that indicates whether a pseudoword is inflected or not (**IsInfl**) was included in the model as well¹². A summary of this model is provided in Table 3.

Both phonological measures are significantly predictive for pseudoword duration. For **PhonND**, the effect of which is visualized in the left panel of Figure 8, durations are shorter with increasing **PhonND**. The effect of **BiphProb** (Figure 8, right panel), on the other hand, is linear but with a substantially reduced effect size and opposite sign: pseudoword duration is longer when phonotactic probabilities are higher. The effects of **PhonND** and **BiphProb** are in general in line with the findings of previous studies. Gahl et al. (2012), for example, examined the effect of **PhonND** on word duration in spontaneous speech. Their hypothesis, which is based on the two-step interactive activation model of lexical access of Dell (1986) and Dell and Gordon (2003), is that denser phonological neighborhood is associated with shorter duration. As argued in Dell and Gordon (2003), phonological neighbors collectively generate support for a target via feedback from phonological segments, but do not

¹²The number of phones does not differ significantly for inflected and uninflected words ($t(9571) = -0.79, p = 0.4$). With regards to the number of syllables, although one might expect inflected pseudowords to have more syllables due to inflection such as [ɪŋ], in fact in the MALD database, uninflected pseudowords have on average a somewhat larger mean syllable count than inflected pseudowords (2.7 vs. 2.3: $t(9571) = 15.80, p < 0.0001$). Hence we conclude that **IsInfl** is not confounded with increased length in phones or syllables.

Table 3: GAM fitted to square-root transformed pseudoword duration with the phonological measures as predictors. s: thin plate regression spline smooth.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
Intercept	24.0155	0.0287	835.68	< 0.0001
IsInfl:TRUE	0.3693	0.0447	8.263	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(PhonND)	5.365	6.260	937.55	< 0.0001
s(BiphProb)	1.001	1.001	88.36	< 0.0001

-ML = 20876, $R^2(\text{adj}) = 0.396$

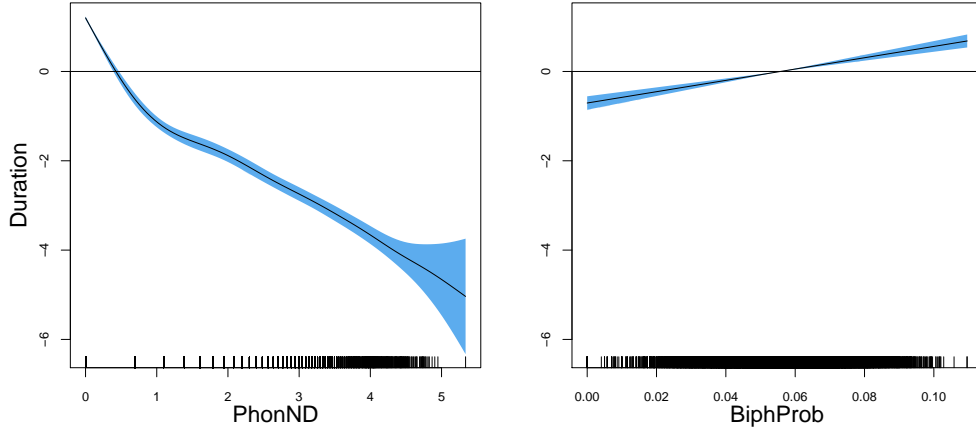


Figure 8: The partial effects of the phonological measures on square-root transformed pseudoword duration.

constitute target competitors: The target gets strong semantic support during early (semantically-driven) stages of lexical selection, which the phonological neighbors lack. Such a shortening effect of **PhonND** on duration was confirmed by their study for words, as well as the present study for pseudowords¹³. With regards to **BiphProb**, although the investigation of its effect in [Gahl et al. \(2012\)](#) is less direct, due to its high correlation with **PhonND** ($r = 0.62$), they reported a marginal trend for larger **BiphProb** (after residualization on **PhonND**) leading to longer duration. For the pseudowords examined here, the two measures are not correlated ($r = -0.13$), possibly due to a wider range of pseudoword lengths and syllable structures in the current dataset. Nevertheless, we similarly observed a lengthening effect of **BiphProb** on duration.

A second GAM was fitted to pseudoword duration with the LDL measures as predictors. However, as shown in Table 2, these predictors are highly correlated with one another. For example, for **EDNN** and **NNC**, $r = -0.45$ for the direct route and -0.46 for the indirect route. For **NNC** and **ALC**, $r = 0.57$ and 0.68 respectively. Moreover, the two-route correlations for these three measures are as high as 1, 0.62, and 0.87. Given the high correlations among the LDL predictors ($\kappa = 159.91$), especially those derived from the comprehension model, we performed a Principal Component Analysis

¹³About 63% of the pseudowords do not have any phonological neighbors (cf. upper left panel, Figure 7). Results remain largely the same when the pseudowords without any phonological neighbors are excluded from the dataset.

(PCA) regularization on the subset of semantic measures ($EDNN_1$, NNC_1 , ALC_1 , $EDNN_2$, NNC_2 , ALC_2 , DRC)¹⁴. The newly derived orthogonal dimensions (PCs) were predictive for acoustic durations to a substantial extent. However, because of the complicated inter-relations among these measures, these PCs were uninterpretable. Subsequent analyses revealed that the results of regression analyses stayed qualitatively the same when we used only measures from one of the two routes, unsurprisingly given the high similarity of the semantic vectors estimated by the two routes (cf. Figure 7). Although overall model fit is slightly better with the omnibus analysis, for being able to interpret the effects of these semantic measures, we opted to use only predictors derived from the direct route (i.e., $EDNN_1$, NNC_1 , ALC_1), and to rely on DRC to inform us about how similar the predictions generated by the two routes are.

Even with only measures from the direct route, the model is still beset with high collinearity ($\kappa = 139.73$). We thus again performed PCA on $EDNN$, NNC , ALC (of the direct route), and DRC . The PCA loadings for these four measures are shown in Table 4. To illustrate the relation between PCs and the original measures, Figure 9 presents the original values of the four measures of three pseudowords: [ɪsɛtnəfə], [wɑɪpiə], and [əskæfɪŋti], which have high PC1, PC2, and PC3 values respectively. Table 4 shows that PC1 contrasts $EDNN$ with the other three measures. When PC1 is large (Figure 9, top panels, illustrates this for the pseudoword [ɪsɛtnəfə]), a pseudoword is distant from other words (high $EDNN$), not semantically similar to any word (low NNC), and lands in a sparse neighborhood (low ALC). At the same time, the semantic predictions of the two routes are dissimilar (low DRC). In Figure 9 (top center panels), this is illustrated by the separation of the dashed vertical lines representing the direct and the indirect routes. In other words, a pseudoword with a high value of PC1 has ended up in a semantically isolated region without many surrounding word neighbors, although exactly where the pseudoword is located seems to be route-dependent.

PC2, on the other hand, contrasts DRC primarily with ALC . A pseudoword with a large PC2 value (Figure 9, mid panels, illustrates this for the pseudoword [wɑɪpiə]) is again in a sparse neighborhood (low ALC), but both the direct and indirect routes produce similar semantic vectors (high DRC). Both routes predict a relatively sparse semantic neighborhood for the pseudoword, but it is still likely to have a close word neighbor nearby.

As for PC3, this orthogonalized dimension aligns $EDNN$ with DRC . Similar to PC1, larger values of PC3 (Figure 9, bottom panels, illustrates this for the pseudoword [əskæfɪŋti]) again indicate that a pseudoword is very distant from its nearest neighbor (high $EDNN$). However, unlike PC1, the meanings generated by the two routes are similar (high DRC). This suggests that the pseudoword again lands in a far-away semantic space, but both routes yield very similar predictions.

The three PCs together account for 90% of the variance in the semantic measures. With the three PCs, the condition number for all the LDL predictors together (PC1, PC2, PC3 and the two production measures $ALDC$ and $SCPP$) is reduced to an acceptable value ($\kappa = 12.20$). In our analysis we included one factorial predictor, $IsInf1$, a binary variable indicating the presence of a potential inflectional ending, that we also used in the analysis of standard phonological measures

¹⁴For strategies dealing with collinearity, see [Tomaschek et al. \(2018\)](#).

Table 4: PCA loadings for the four semantic measures.

	PC1	PC2	PC3
EDNN	0.49	-0.29	0.78
NNC	-0.59	-0.24	0.03
ALC	-0.50	-0.59	0.28
DRC	-0.41	0.72	0.56

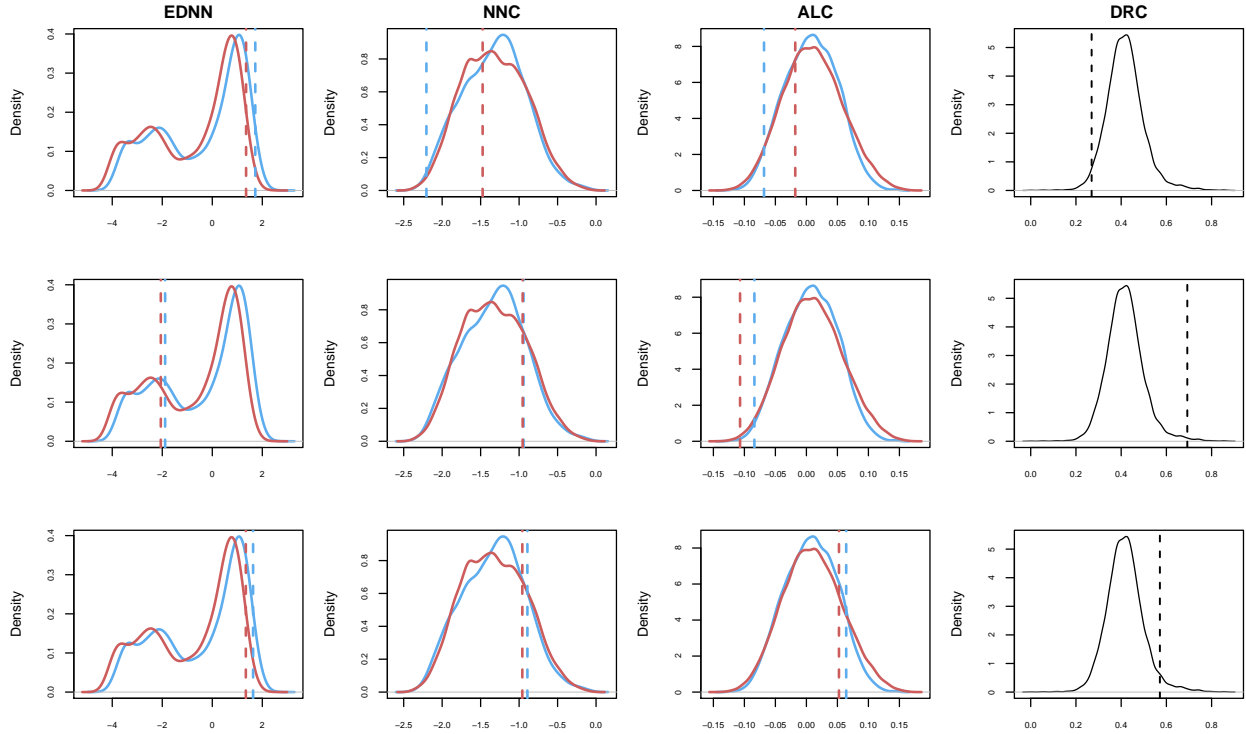


Figure 9: The values of the four semantic measures for three pseudowords: [ɪsɛtnəfə] (top), [wɑɹpiə] (mid), and [əskæfɪŋti] (bottom), which have high PC1, PC2, and PC3 values respectively. The dashed lines highlight the position of the three words with respect to distributions. The blue lines are for the direct route, while the red lines are for the indirect route. The upper left panel shows that [ɪsɛtnəfə] has a high value for EDNN, and hence, given Table 4, has a high value on PC1.

(see Table 3).

In the following analyses, we included not only the production measures but also the comprehension measures for predicting the acoustic durations of pseudowords. The reasons for including comprehension measures are two-fold. First, the speaker was requested to name pseudowords from IPA transcriptions multiple times. Given that he heard himself saying the pseudowords, a comprehension component is therefore inevitably involved in his production. In addition, the effect of phonology on reading has been well documented (Wong and Chen, 1999; Newman et al., 2012; Jared et al., 2016; Jared and Bainbridge, 2017), and even for silent reading, readers usually hear their “inner voice” (Perrone-Bertolotti et al., 2012). Our model explicitly takes these complex in-

interactions between comprehension and production into account in a principled way. Second, the LDL model assumes that speech production involves internal comprehension loop, implementing “synthesis-by-analysis”; for extensive discussion and motivation, see [Baayen et al. \(2018a\)](#). The SCPP measure gauges the consequences of the internal comprehension process guiding production (see [Hickok, 2014](#), for neuro-cognitive evidence for interaction between the comprehension and the production systems).

The model summary is presented in Table 5. All LDL measures are reliable predictors for pseudoword duration. We first consider the two measures derived from the production model, the partial effects of which are shown in the lower panels of Figure 10. For ALDC, the positive effect on pseudoword duration is nearly linear with a large effect size. As the candidate forms generated by the model (on the basis of the internal conceptualization of a pseudoword’s meaning) are more distant from the intended pronunciation of a pseudoword, its duration tends to be longer. With respect to SCPP, which gauges the semantic correlation between the form realized by the speaker and the best candidate form given its perceived semantics, we again observe a positive, but substantially attenuated and non-linear effect on duration. For real words, two studies, [Kuperman et al. \(2006\)](#) and [Cohen \(2014\)](#), have reported acoustic strengthening in conditions with reduced uncertainty. We interpret the effects of ALDC and SCPP in the same way. When the predicted pseudoword form is not confusable with other forms, and when there is little discrepancy between the semantics projected by the spoken form and the form generated from its semantics, durations increase.

The upper panels of Figure 10 visualize the effects of these three PCs. For PC1, larger values give rise to longer duration, indicating that when a pseudoword is semantically at a greater distance from its word neighbors and semantically not very confusable with real words, its duration tends to be lengthened. PC1 may be capturing pseudowords that stand out semantically as pseudowords, similar to the way in which a novel taste can stand out as distinct from previously experienced tastes. This effect mirrors that of ALDC, in that the general trends have positive slope.

Larger PC2 values, on the contrary, lead to shorter duration. This depicts a situation where the semantics estimated by the two routes converge, but where the pseudoword is in a sparse neighborhood. PC3 shows an upward trend similar to PC1, but with a stronger effect size. When PC3 is larger, it is again the case that the semantics of the two routes converge, but now the pseudoword is farther away from its nearest neighbor. Apparently, PC2 and PC3 are gauging two opposite orthogonal effects in the presence of route convergence, that differentiate between semantic density and semantic distance. It thus appears that on the one hand, route convergence can be beneficial, in the sense that a consistent interpretation is obtained. This effect is conditioned by large semantic distance of the pseudoword from other words. In this case, PC3 affords durational lengthening. On the other hand, when in a sparse neighborhood, the similarity of two meanings would increase entropy in the system, leading to durational shortening (PC2).

Compared to the GAM with the standard phonological measures as predictors, the model fit of the model with the LDL measures is substantially better, indicated by a decrease of ML scores by 1913. However, if we add the two standard phonological measures as additional predictors to

Table 5: GAM fitted to square-root transformed pseudoword duration with the LDL measures as predictors. s: thin plate regression spline smooth.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
Intercept	24.0092	0.0238	1010.7	< 0.0001
IsInfl:TRUE	0.3844	0.0375	10.26	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(PC1)	3.065	3.889	161.6	< 0.0001
s(PC2)	1.001	1.001	173.0	< 0.0001
s(PC3)	1.000	1.000	792.8	< 0.0001
s(ALDC)	3.279	4.150	1495.6	< 0.0001
s(SCPP)	7.656	8.555	141.7	< 0.0001

-ML = 18963, $R^2(\text{adj}) = 0.596$

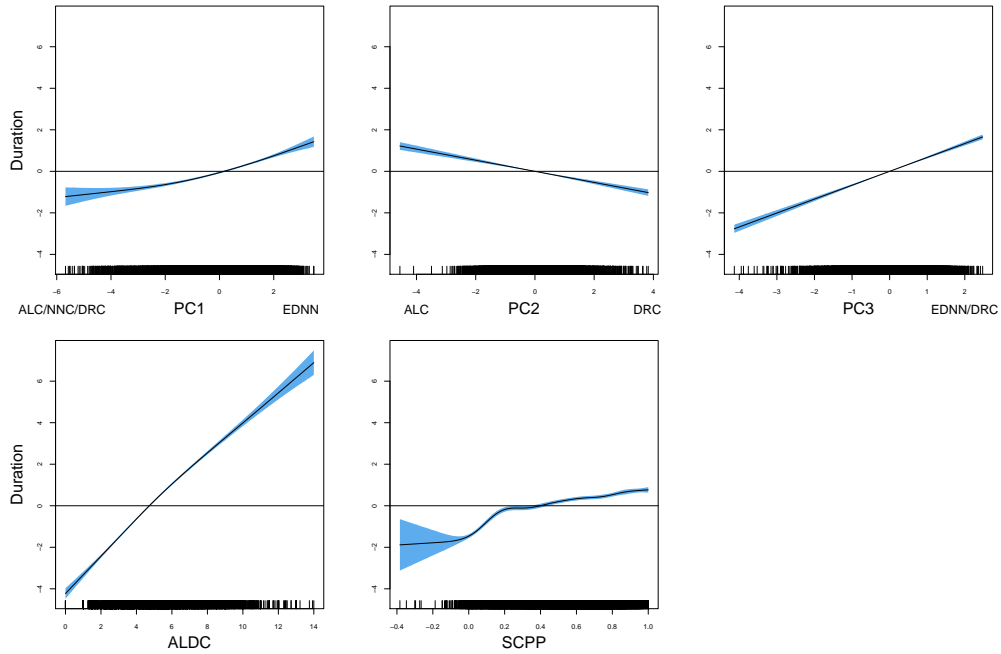


Figure 10: The partial effects of the LDL measures on square-root pseudoword duration. For each of the PCs (upper panels), measures with positive loadings on a PC are indicated at the higher end of the scale, whereas measures with negative loadings are indicated at the lower end.

the latter model, model fit still improves (ML scores decrease by 296.71), but the effect sizes of the two phonological measures are substantially attenuated. While larger **PhonND** again leads to shorter duration (similar to Figure 8, left panel), the effect of **BiphProb** levels off with a tiny effect size. It thus seems that part of the **PhonND** effect and almost the entire **BiphProb** effect have been captured by the LDL measures. We will return to the theoretical consequences of the remaining effect of phonological neighborhood density in the general discussion.

Table 6: GAMM fitted to pseudoword Box-Cox transformed RT with the phonological measures as predictors. s: thin plate regression spline smooth.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
Intercept	5231.12	29.34	178.30	< 0.0001
IsInfl:TRUE	-15.487	7.21	-2.15	< 0.05
B. smooth terms	edf	Ref.df	F-value	p-value
s(PhonND)	5.495	5.804	550.410	< 0.0001
s(BiphProb)	3.579	3.892	5.118	< 0.001
s(Subject)	227.98	230	176.177	< 0.0001
s(Pseudoword)	6218.92	9569	7.461	< 0.001
fREML = 159885, $R^2(\text{adj}) = 0.324$				

5.3 Pseudoword reaction time

The original data of pseudoword RTs provided by the MALD database were measured from stimulus onset. Given that this RT measure includes duration, it is unsurprising that duration and RT are well correlated ($r = 0.37$). In fact, duration is the dominant predictor for RT. To avoid issues of collinearity, specifically arising here because duration itself is co-determined by the present predictors, we subtracted duration from reaction time, focusing on RT measured from pseudoword offset. About 1.2% of the offset RTs are negative, indicating early responses before offset. These tokens were excluded from the analyses.

Due to the very positively skewed distribution of RTs, we applied a Box-Cox transformation to RTs with a λ value of 0.26. As for the duration analyses, we first fitted a GAMM to RTs with the two phonological measures as predictors. The indicator variable for inflection, **IsInfl**, along with by-subject and by-pseudoword random intercepts, were included as well. A model summary is provided in Table 6. Both phonological effects are significant, but the roughly linear effect of **PhonND** is much stronger than the small U-shaped effect of **BiphProb** (see Figure 11). This pattern of results fits well with the finding of Vitevitch and Luce (1999) that the perception of pseudowords in a lexical decision task is primarily determined by the effect of **PhonND**. According to Vitevitch and Luce, because the task of lexical decision requires listeners to explicitly distinguish pseudowords from words, pseudowords with more phonological neighbors, which induce more severe lexical competition, are thus more difficult to reject.

A second GAMM was fitted to predict RTs from the same LDL measures that we used for modeling acoustic durations. A summary of the model is presented in Table 7. For the three PCs (Figure 12, upper panels), the effects are mostly linear or close to linear. PC1 has a negative effect on RTs, with larger PC1 values leading to shorter RTs. Thus, response times are reduced when a pseudoword is semantically distinct, i.e., at greater distance from its nearest semantic neighbors. The effect of PC2, on the other hand, exhibits an upward trend, with RTs becoming longer as PC2 increases. Finally for PC3, as for PC1, a downward trend is present.

The two measures from the production part of the model (Figure 12, lower panels) also account for the variance in the RTs to a substantial extent. **ALDC** has a robust effect on RTs, with larger **ALDC**

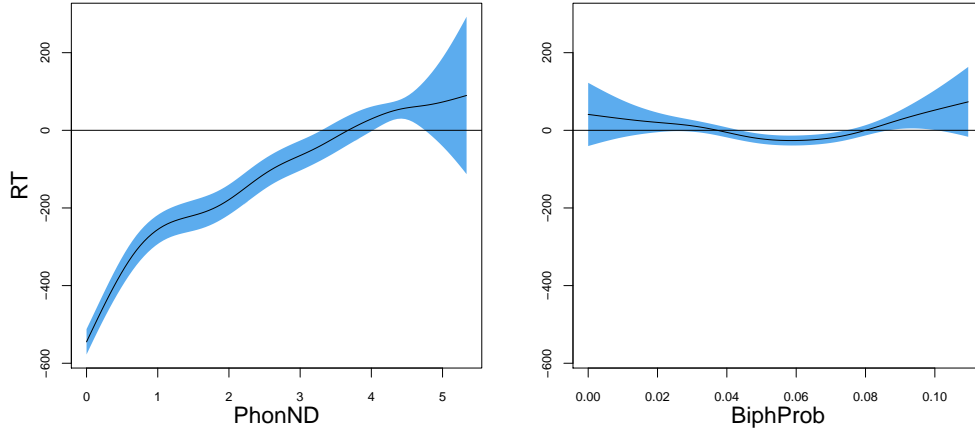


Figure 11: The partial effects of the phonological measures on Box-Cox transformed pseudoword RT.

Table 7: GAMM fitted to Box-Cox transformed pseudoword RT with the LDL measures as predictors. s: thin plate regression spline smooth.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
Intercept	4731.07	25.85	183.0	< 0.0001
IsInfl:TRUE	-23.21	7.03	-3.3	< 0.001
B. smooth terms	edf	Ref.df	F-value	p-value
s(PC1)	2.770	3.051	44.643	< 0.0001
s(PC2)	1.013	1.018	44.579	< 0.0001
s(PC3)	1.002	1.002	139.552	< 0.0001
s(ALDC)	4.643	5.046	438.29	< 0.0001
s(SCPP)	6.135	6.559	51.12	< 0.0001
s(Subject)	227.00	230.00	170.43	< 0.0001
s(Pseudoword)	5870.70	9566	6.368	< 0.0001

fREML = 158846, $R^2(\text{adj}) = 0.325$

values leading to shorter RTs. As to **SCPP**, its effect, similar to that of **ALDC**, exhibits a downward trend, but it is more non-linear and its effect size is smaller. Generally, the effects on RTs are near mirror images of the effects on duration. Apparently, the same factors driving durational lengthening for the speaker allow listeners, after stimulus offset, to quickly reject pseudowords as real words.

With the LDL measures, model fit again significantly improved compared to the model with standard phonological predictors, with fREML scores decreasing by 1039 units. Although the inclusion of **PhonND** and **BiphProb** into the current model still improved model fit (Δ fREML = 351.2 units), their effect sizes were substantially reduced.

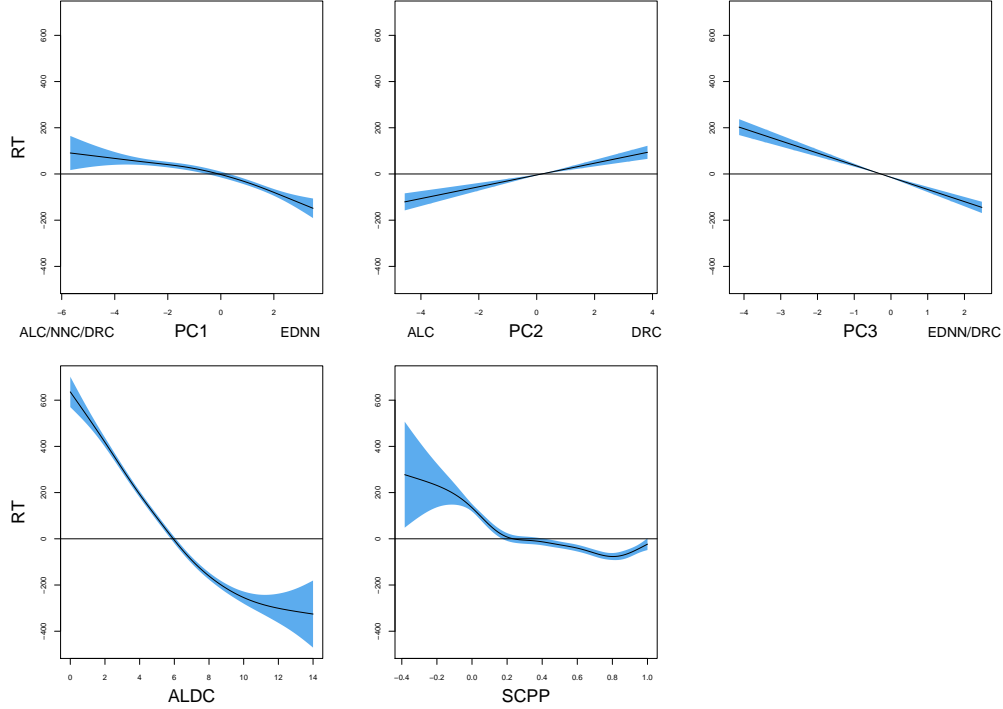


Figure 12: The partial effects of the LDL measures on Box-Cox transformed pseudoword RT. For each of the PCs (upper panels), measures with positive loadings on a PC are indicated at the higher end of the scale, whereas measures with negative loadings are indicated at the lower end.

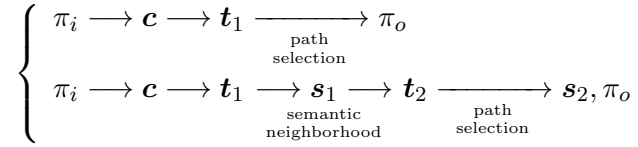


Figure 13: LDL processing stages. π_i represents spatially or temporally ordered visual or auditory input. \mathbf{c} represents a modality-specific cue vector, \mathbf{t} denotes a triphone vector, \mathbf{s} is a semantic vector, and π_o denotes an ordered sequence of triphones that is the input for articulation. The upper flow denotes naming bypassing semantics, the lower flow represents naming, comprehension, and production with semantics. Semantic measures (EDNN, NNC, ALC) quantify the semantic neighborhood of \mathbf{s}_1 . The ALDC measure quantifies path selection, and the SCPP measure is the correlation of \mathbf{s}_1 and \mathbf{s}_2 . The direct route in comprehension bypasses \mathbf{t}_1 .

6 Discussion

In this study we made use of the LDL framework to model the production and perception of auditory pseudowords. The relevant processing stages, summarized in Figure 13, can be grouped into two pathways (cf. Coltheart et al., 1993, 2001). The upper pathway does not involve semantics. The visual input (π_i), which is a sequence of letters ordered in space, is transformed into an unordered visual cue vector (here of IPA triphones) \mathbf{c} , which is then mapped onto a triphone vector \mathbf{t}_1 , representing the internal auditory image of the pseudoword. Because there is a one-to-one mapping

between the IPA transcriptions read by the speaker and the triphones in \mathbf{t}_1 , the path selection algorithm operating on \mathbf{t}_1 performs nearly error-free: when the threshold for thinning the triphone graph is set close to 1, there typically is only one candidate path. In this way we model that the speaker nearly always produce the targeted pseudowords from print.

What is central to the current study is the lower processing path depicted in Figure 13, which does involve semantics, and which we assume to proceed in parallel with the upper path. For production driven by internal conceptualization, the production process starts at the semantic vector \mathbf{s}_1 . This vector is mapped onto the triphone vector \mathbf{t}_2 , from which our path selection algorithm selects the best path. This algorithm implements synthesis-by-analysis for selecting the best path. The best path is that path for which the corresponding predicted semantic vector (\mathbf{s}_2) is closest to the targeted semantic vector (\mathbf{s}_1). This path (π_o) in turn drives articulation.

For the naming of real words, the triphone vector \mathbf{t}_1 is assumed to be mapped into the semantic space. This mapping is independently required for not only production but also comprehension with the indirect route. The resulting semantic vector \mathbf{s}_1 then passes through the production process as described above. For real words, the mappings both onto \mathbf{s}_1 and subsequently onto \mathbf{t}_2 are well learned, such that the input for articulation (π_o) will typically match the output from the direct naming route (the upper path in Figure 13). However, for pseudowords, this is not necessarily the case: the predicted semantic vector \mathbf{s}_1 typically lands in a region of semantic space where it is not that close to the semantic vectors of real words. Furthermore, in the synthesis-by-analysis process, the paths that are predicted from this semantic vector in turn predict semantic vectors that are not very close to the semantic vector \mathbf{s}_1 that is to be realized in speech. This holds even for the semantic vector \mathbf{s}_2 , which is the most similar to the targeted semantic vector \mathbf{s}_1 .

With respect to auditory comprehension, for which semantics is always involved, only the lower path is at play. The temporally ordered auditory input is transformed into an unordered FBS feature vector \mathbf{c} . Depending on which route is taken, \mathbf{c} is mapped onto the semantic vector \mathbf{s}_1 either directly or indirectly via the triphone vector \mathbf{t}_1 . This is usually the end stage of processing in classical models of auditory comprehension. However, in our model, the comprehension and production systems interact such that the semantic vector \mathbf{s}_1 is subsequently mapped onto a triphone vector \mathbf{t}_2 , which in turn leads to the activation of the semantic vector \mathbf{s}_2 . For real words, the processing steps are well learned, and \mathbf{s}_2 will be similar or identical to \mathbf{s}_1 . Thus little uncertainty arises in the system. By contrast, pseudowords give rise to much more uncertainty. The semantic vectors \mathbf{s}_1 and \mathbf{s}_2 will be typically much less similar than in the case of real words. As a consequence, the measures for semantic neighborhood and path selection are much more informative for pseudowords as compared to words.

Thus, it is specifically for pseudowords that measures of semantic neighborhood, as well as measures of path selection uncertainty can be predictive for speak production, as gauged by acoustic durations, and for auditory comprehension, as gauged by auditory lexical decision latencies.

A further consideration is that pseudowords do not have the rich semantics that characterizes real words. They land in an area of semantic space that does not link up to discriminated exper-

iences of the world. This explains why upon reading or hearing a pseudoword, there is no clear semantic percept that reaches awareness. However, subliminal semantic processing does take place, as evidenced by the predictivity of our semantic and production measures. We suspect that for real words the clarity of the semantic percept and its link to real world knowledge may largely mask the effect of the resonance between the production and comprehension systems. If this conjecture can be shown to be correct, the implication is that pseudowords are especially felicitous tool for investigating this resonance experimentally.

The results obtained in this study have several implications for the theory of the mental lexicon. First, instead of taking production and comprehension to be mechanical processes that are independent of each other, LDL implements a model in which the two subsystems resonate, and in which forms and meanings emerge out of the ‘negotiations’ between these subsystems.

Second, pseudowords clearly are not semantically empty. In fact, this conclusion is not new in linguistics. The meaning of sublexical units has been extensively discussed in the literature of sound symbolism (e.g., Köhler, 1929; Sapir, 1929; Westbury, 2005; Maurer et al., 2006; Imai and Kita, 2014; Westbury et al., 2018), providing evidence that pseudowords are to some extent interpreted. In the domain of computational modeling research, however, the possibility that pseudowords might have their own specific semantics has not been explored. The focus has been on distinguishing words from pseudowords either on the basis of the properties of activation patterns (e.g., McClelland and Rumelhart, 1981; Grainger and Jacobs, 1996), or on the basis of a hypothesized general nonword node or representation (Norris and McQueen, 2008).

Third, the mappings learned between form and meaning in LDL enable morphological effects to emerge straightforwardly. With respect to the pseudowords in our data which potentially carry inflectional exponents, we found that they are to some extent semantically distinct from those pseudowords that do not have inflectional exponents. Furthermore, pseudowords are semantically more similar to words and pseudowords carrying the same inflectional exponents, as compared to words and pseudowords with different inflectional exponents. This suggests that these pseudowords are projected into semantic subspaces populated with semantic vectors of inflectionally related words. We note that for inflected pseudowords, the semantics of the pseudoword stems still remain relevant — otherwise, the semantic vectors of inflected pseudowords would be identical for all pseudowords with the same exponent, contrary to fact. From this, we conclude that auditory comprehension of morphologically complex words is algorithmically possible without ever having to parse the speech signal into discrete pre-existing constituents. In other words, our results demonstrate that pseudowords can be processed morphologically without mediation by morpheme units. This strengthens the case, made by Baayen et al. (2019), that real words are also produced and understood without the involvement of morpheme units.

Fourth, the semantic and formal neighborhood structures of pseudowords co-determine pseudoword processing. To gauge semantic neighborhood properties, we calculated both the Euclidean distance and the angles between semantic vectors (EDNN, NNC, ALC). As to form neighborhood, here we calculated the average distance between the targeted pronunciation form and the can-

didate forms generated by the path selection algorithm (ALDC). While these neighborhood effects receive robust statistical support, they however require further discussion in the context of the LDL framework. This framework, as laid out in Figure 1, comprises a set of inter-connected networks (implemented with linear mappings). Exemplars leave traces in these networks, but are not stored as such. They exert their influence during learning, but do not have an independent ontological status. Although we define matrices such as \mathbf{C}_a , \mathbf{C}_o , \mathbf{S} , and \mathbf{T}_a , the rows of which specify properties of exemplars, these matrices also do not have independent ontological status. It is for computational convenience that in the present study we use linear algebra to estimate the mappings. In theory, learning is incremental. Incremental learning of linear mappings is possible with the update rule of Widrow and Hoff (1960), but for the relatively small training set of the MALD real words, however, the estimation method using linear algebra is both efficient and precise. Conceptually, LDL is an exemplar-free model.

This raises the question of how the measures derived from the model, which make reference to neighbors, should be understood. For semantic neighbors (on which the EDNN, NNC, ALC, and DRC measures are based), our tentative answer to this question builds on the hypothesis that a semantic vector is not a goal in itself, but rather that a semantic vector makes further contact with words' affordances (Gibson, 1977). Neighbor vectors thus provide glimpses of the kind of affordances that a pseudoword is co-activating to some extent. By way of example, consider a blend such as *brunch*, and suppose that this blend has not been encountered before. Suppose its semantic vector is in the proximity of the semantic vectors of *breakfast* and *lunch*. The vectors $\overrightarrow{\text{breakfast}}$ and $\overrightarrow{\text{lunch}}$ make contact with typical meals and the time of day for which these meals are scheduled. By considering the proximity of $\overrightarrow{\text{brunch}}$ to $\overrightarrow{\text{lunch}}$ and $\overrightarrow{\text{breakfast}}$, we are in fact assessing to what extent the affordances provided by the neighbors make sense. For *brunch*, a blend that was created in England in the late 19th century, a sensible merger of affordances has led to the interpretation of a combined breakfast and lunch, eaten in the late morning or early afternoon (see Gries, 2004, for discussion of what makes blends successful). Thus, if a pseudoword vector lands in a sparsely populated area in semantic space, little contact is made with existing affordances, and the affordances of the distant neighbors will be more diverse and more difficult to make sense of. Such a state of affairs leads to fast rejection times in auditory lexical decision and to longer acoustic durations in speech production.

Form neighbors come into play with the ALDC measure. This measure evaluates the similarity of the pseudoword form produced with the neighbors projected from the pseudoword's semantic vector. We do not take these form neighbors to be competing lexical entries. We think of them more as alternative realizations that are also supported to some extent by the semantics of the pseudoword. These neighbors are rather similar to pronunciation variants or speech errors, such as English *blazed* being realized with final /zɪd/ instead of /zɪd/, or *mouths* being realized with as coda /θs/ instead of /ðz/. Thus, the ALDC measure provides a means for assessing the uncertainty about the proper form of a pseudoword given its meaning. Greater values of ALDC are indicative of neighbors being less similar. Reduced neighbor similarity implies decreased lexical uncertainty, and

this in turn affords shorter reaction times and longer durations.

Although a regression model with LDL predictors provides a more precise fit to the reaction times and acoustic durations compared to a regression model with classical measures of lexical similarity, we observed above that adding the neighborhood density measure as an additional predictor to the LDL regression model results in a further improvement in goodness of fit. This result suggests that we are still missing out on an important aspect of lexical similarity. Our current hypothesis is that this is due to the LDL model being deterministic rather than stochastic. Model input is represented by vectors of units that are either on or off. In real biological systems, what we represent with a unit for the presence or absence of a feature is in reality an assembly of cells each of which is more or less likely to fire given some input. Furthermore, synaptic connectivity has also been observed to be stochastic (see [Kappel et al., 2015, 2017](#), for error-driven learning models with stochastic connection weights). To make the LDL model more realistic, a deterministic form representation will have to be replaced by a distribution of form representations, and a deterministic linear mapping will likewise require replacement by a stochastic linear mapping. The result of a form-to-meaning mapping will thus be a distribution of semantic vectors. Our hypothesis is that neighborhood similarity effects are intrinsic to stochastic systems, and that ‘neighbors’ are actually less probable network states in a superposition of network states in which the targeted state is (ideally) the most probable one. We leave the formalization of this intuition, which could be pursued within a Bayesian framework (see, e.g., [Kappel et al., 2015](#)) or using methods from quantum physics (for an implementation of an exemplar model using quantum computing, see [Skousen, 2000](#)) to future research.

Finally, this study is not the first to demonstrate that the processing of pseudowords may involve semantics (see, e.g., [Cassani et al., 2019](#)). In the context of the present study, the investigation by [Hendrix \(2019\)](#) of the processing of pseudowords in the visual lexical decision task is of special interest. Similar to our study, he also generated semantic vectors for pseudowords, though using a different computational method (fastText, [Bojanowski et al., 2017](#)), and calculated the angles between the semantic vectors of pseudowords and those of words. He found that pseudowords that are semantically more dissimilar to real words are rejected more quickly, which is consistent with our findings for auditory pseudowords. In addition to pseudoword semantics, he further observed an effect of pseudoword frequency. Interestingly, nearly all of the pseudowords he examined (a subset from the British Lexicon Project, [Keuleers et al., 2012](#)) have a non-zero frequency count according to a Google search. These pseudoword frequency counts appear to have a non-negligible effect on visual pseudoword processing, with greater frequencies predicting longer rejection times. The potential effect of frequency on auditory pseudoword processing is an interesting topic worth further pursuit. However, given that orthographic information is not available for pseudowords in the MALD database, and given the amount of irregularity in the sound-spelling correspondence in English, it is unclear how to best estimate the frequency of auditory pseudowords. Nevertheless, in light of these accumulating results, it is now becoming clear that much more can be said about pseudoword processing than previously assumed, and that even more remains to be discovered.

Appendix

LDL with tweet-based Word2Vec embeddings

To test whether the above results are specific to the NDL-based semantic vectors that we used, a separate analysis was carried out by using a different algorithm for constructing semantic vectors, applied to a different language register. We downloaded the word embeddings from <https://www.spinningbytes.com/resources/wordembeddings/> (Cieliebak et al., 2017; Deriu et al., 2017). These embeddings are 200-dimension vectors, which were trained with Word2Vec on 200 million English Tweets. For the MALD words, 26,283 embeddings are available in this resource, resulting in a $26,283 \times 200$ semantic matrix \mathbf{S} . Note that inflectional homographs are not distinguished, and receive exactly the same embedding (that is, the verb *walks* and the noun *walks* are treated identically). Following the same procedures as described above, we built both a production and comprehension model. Again two estimated semantic vectors were derived for each pseudoword, one based on the direct route and the other based on the indirect route.

The first question is whether inflectional semantics can be captured by the networks trained with the Word2Vec-based embeddings. To address this issue, we again examined whether pseudowords labeled with a given inflectional function are semantically more similar to those with the same inflectional function, as compared to those with different inflectional functions or uninflected pseudowords. As highly similar patterns emerge for the two routes, Figure 14 only presents boxplots for the correlations derived from predictions of the direct route. For COMPARATIVE and CONTINUOUS pseudowords, correlations with pseudowords of the same function are indeed higher than those of different functions, and higher also for uninflected pseudowords. However, for the other three inflectional functions, higher within-group correlations are not found. For PERSON3/PLURAL pseudowords, the effect is in the opposite direction: they are more correlated with, and thus semantically more similar to, the non-PERSON3/PLURAL inflected pseudowords and uninflected pseudowords. We conclude that from a morphological perspective, the Tweet-derived Word2Vec embeddings perform less well compared to the semantic vectors developed in Baayen et al. (2019) and that we used above.

We then calculated all the semantic and form measures exactly as defined above. As before, the distributions of the measures calculated from the two routes were very similar, details are available in the supplementary materials. A comparison of the measures obtained with Word2Vec and those obtained with NDL reveals very high correlation for the two distance measures (EDNN_1 and EDNN_2), see Table 8. The angle measures MNC and ALC , as well as the DRC measure, were less similar. With respect to the two production measures, whereas ALDC is very similar for the two embeddings, SCPP , on the other hand, show no correlation. In fact, the two production measures for the Word2Vec-based embeddings are not very reliable, since the production algorithm, even with a threshold for thinning the triphone graph lowered from 0.1 to 0.05, still failed to generate pronunciations for over half of the pseudowords (54%). This only happens for less than 10% of the pseudowords for the network

Table 8: Spearman’s correlations between measures derived from networks using NDL and Word2Vec embeddings.

EDNN ₁	EDNN ₂	NNC ₁	NNC ₂	ALC ₁	ALC ₂	DRC	ALDC	SCPP
0.94	0.94	0.38	0.39	0.24	0.29	0.20	0.75	-0.05

using NDL semantic vectors. This is likely to be due to two factors. First, the dimensionality of the Word2Vec embeddings is only 200, whereas the dimensionality of the form space is 8,601, almost two orders of magnitude greater. As a consequence, the precision of the mapping from semantics to forms must lose considerable precision. Second, the vectors in the semantic space set up by Word2Vec are much more similar to each other than is the case for the space set up by NDL (compare Figure 5 and Figure 14). Given the imprecision of the production measures, we considered only the semantic measures in the following regression analyses. Furthermore, as the measures derived from the two routes are so similar, we again used only the measures from the direct route in the statistical analysis.

The high correlations among the semantic measures (e.g., $r(\text{EDNN}, \text{NNC}) = -0.81$, $r(\text{EDNN}, \text{ALC}) = -0.84$, $r(\text{NNC}, \text{ALC}) = 0.89$, and $r(\text{ALC}, \text{DRC}) = 0.65$) necessitated PCA orthogonalization; the first three PCs together accounted for 97.5% of the variance. The new PC1 had loadings that were very similar to the loadings of the NDL-based PC1, and hence has a very similar interpretation. The new PC2 had strong loadings for EDNN and DRC, and hence has a similar interpretation as the original PC3. The new PC3 showed strong loadings for EDNN and NNC, with high values for pseudowords for which the nearest neighbor is at a great distance but with small angle. In what follows we only report the model fitted to acoustic durations, as the pattern of results for reaction times is the

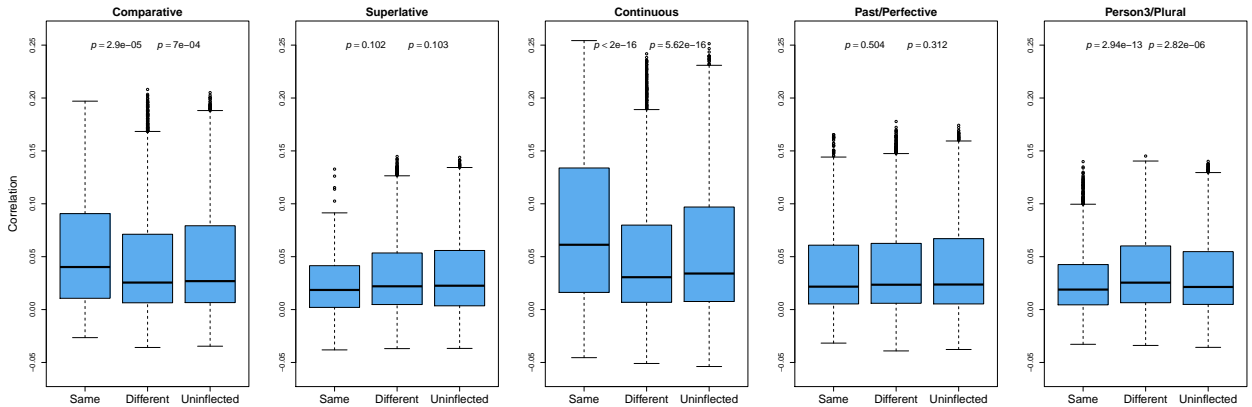


Figure 14: Boxplots of inflected pseudowords’ correlations with other pseudowords of the same, different inflectional categories, and with uninflected pseudowords. The semantic vectors of pseudowords are derived from the direct route, based on Word2Vec embeddings. The p values in the graphs are taken from regression models in which correlations are predicted by different inflectional categories. The first p value is for the comparison between Same and Different categories, and the second one is for that between Same and Uninflected categories.

Table 10: GAM fitted to square-root transformed pseudoword duration with NDL-based semantic measures as predictors. s: thin plate regression spline smooth.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
Intercept	24.1695	0.0234	1032	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(PC1)	3.120	3.956	439.4	< 0.0001
s(PC2)	1.007	1.015	377.9	< 0.0001
s(PC3)	5.439	6.662	297.7	< 0.0001

-ML = 21533, $R^2(\text{adj}) = 0.308$

mirror image of that for the durations.

A summary of the GAM fitted to the acoustic durations is provided in Table 9. Clearly, the model with measures obtained with **Word2Vec** applied to Tweets is also predictive for pseudoword duration. Nevertheless, the model fit is slightly worse compared to that of the corresponding model with NDL-based measures as predictors (Table 10), i.e., using only the semantic measures and leaving out the production measures, with a difference of 18.42 AIC units. From this we conclude, first, that the NDL-based semantic vectors and the **Word2Vec**-based vectors generate similar predictions; and second, that the NDL-based measures do not perform worse, and may actually perform slightly better. We note here that Baayen et al. (2019) provide extensive validation of NDL-based semantic vectors, and that a comparison of the performance of NDL-based and **Word2Vec**-based modeling (Long, 2018) clarified that both methods have their advantages and disadvantages, a result which is in line with recent findings in computational linguistics (Melamud et al., 2016).

Table 9: GAM fitted to square-root transformed pseudoword duration with **Word2Vec**-based semantic measures as predictors. s: thin plate regression spline smooth.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
Intercept	24.1695	0.0235	1031	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(PC1)	5.372	6.549	516.7	< 0.0001
s(PC2)	1.001	1.002	487.2	< 0.0001
s(PC3)	1.003	1.005	326.9	< 0.0001

-ML = 21540, $R^2(\text{adj}) = 0.306$

7 Open Practices Statement

This study makes use of the MALD data, see Tucker et al. (2018, available at <http://mald.artsrn.ualberta.ca>). Software for LDL is available at http://www.sfs.uni-tuebingen.de/~hbaayen/publications/WpmWithLdl_1.0.tar.gz. No experiments were run and hence no pre-registration could have been implemented.

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