

How the brain composes morphemes into meaning

Laura Gwilliams

Psychology Department, New York University, USA

Abstract

Morphemes (e.g. [tune], [-ful], [-ly]) are the basic blocks with which complex meaning is built. Here I explore the critical role that morpho-syntactic rules play in forming the meaning of morphologically complex words, from two primary standpoints: i) how semantically rich stem morphemes (e.g. explode, bake, post) combine with syntactic operators (e.g. -ion, -er, -age) to output a semantically predictable result; ii) how this process can be understood in terms of mathematical operations, easily allowing the brain to generate representations of novel morphemes and comprehend novel words. With these ideas in mind, I offer a model of morphological processing that incorporates semantic and morpho-syntactic operations in service to meaning composition, and discuss how such a model could be implemented in the human brain.

Keywords: Morpho-syntax, Semantic composition, Neurolinguistics

1. Introduction

That you are understanding the words on this page; that you can understand me still, when I talk to you in a noisy pub or over the telephone; that you and I are able to use language to communicate at all, usually effortlessly, exemplifies one of the most critical cognitive faculties belonging to human beings. The goal of this paper is to discuss one of the processes that helps to make this feat possible; namely how the brain decodes the meaning of a word from a sequence of morphemes (e.g. [dis][appear][ed])¹.

¹There is still some contention as to whether morphemes are neurally represented. An alternative possibility is that lexical information is represented in terms of whole words: the units that would orthographically be flanked by white space Giraudo and Grainger (2000), Devlin et al. (2004). However, given i) the substantial behavioural and neurophysiological evidence that morphemes are in fact represented (for reviews see Rastle and Davis (2008), Amenta and Crepaldi (2012)); ii) the advantage morphological representations provide to speech and text recognition systems (Creutz and Lagus, 2005, Luong et al., 2013, Snyder and Barzilay, 2008, Bojanowski et al., 2017)); iii) the need to move the discussion forward, I take for granted that in representing lexical information, the brain does indeed encode morphological units, likely in combination with, but possibly instead of, morphologically-complex wholes (Marantz, 2013).

9 A morpheme is defined as the smallest linguistic unit that can bear meaning.
 10 The kind of meaning that it encodes depends on what type of morpheme it is.
 11 For instance, *lexical morphemes* primarily encode semantic information (e.g.
 12 [house], [dog], [appear]); *functional morphemes* primarily encode grammatical
 13 or morpho-syntactic information (e.g. [-s], [-ion], [dis-]), such as tense, aspect
 14 and number. In English, these usually map to stem and affix units, respectively,
 15 though this differs considerably cross-linguistically. Each morpheme is an atomic
 16 element, groups of which are combined in order to form morphologically complex
 17 words. For example, to express the process *appear* in the past, one can combine
 18 the stem morpheme with the inflectional suffix *-ed* to create *appeared*; to convey
 19 the opposite, add a negating prefix: *disappeared*.

20 The job of the language listener is to undo the work of the speaker, and
 21 reconstruct the intended meaning from the utterance they are hearing – to
 22 understand the concept *disappeared* rather than to say it (Halle and Stevens,
 23 1962, Bever and Poeppel, 2010, Poeppel and Monahan, 2011). I propose that,
 24 to achieve this, the following processing stages are involved:

- 25 1. **Segmentation:** Identify which atomic units are present.
- 26 2. **Look-up:** Connect each of those units with a set of semantic and/or
 27 syntactic features.
- 28 3. **Composition:** Following the morpho-syntactic rules of the language,
 29 combine those features to form a complex representation.
- 30 4. **Update:** Based on the success of the *sentence* structure, adjust the atomic
 31 representations and combinatory rules for next time.

32 In what follows, I will flesh out each of these processes by introducing a
 33 composite model of morphological processing, reviewing the relevant literature
 34 as I go. In many senses, this builds from previous models of behavioural data,
 35 such as Schreuder and Baayen (1995), updated to incorporate results from neu-
 36 rolinguistics and natural language processing (NLP). I am as explicit as possible
 37 regarding the format of representations at each stage, the transformations ap-
 38 plied, and where in the brain these processes may be happening. Note that I
 39 am not arguing for a strictly serial sequence of operations, such that the pre-
 40 vious stage needs to complete before the next is initiated. Indeed, it is likely
 41 that operations unfold under a more cascaded architecture, such that many
 42 computations occur in parallel (e.g. see Gwilliams et al. (2018)).

43 Ultimately, by the end of this paper, I hope to leave the reader with an an-
 44 swer to two main questions: How are morphological units neurally represented
 45 – in what form, and at what stages of processing? What combinatoric oper-
 46 ations are applied to those representations in order to derive the meaning of
 47 morphologically complex words? In this sense, then, the discussion will focus
 48 on the representational and algorithmic level of analysis, as defined by David
 49 Marr (Marr, 1982). I will focus on the operations that sub-serve language com-
 50 prehension over production, but the review covers research from both domains.

51 2. Composite model of morphological processing

52 The model outlined here draws upon literature from cognitive neuroscience,
53 linguistics and natural language processing (NLP). Combining insight from these
54 approaches is potentially very powerful, as each field is essentially tackling the
55 same problem from differing standpoints. For example, in NLP, the goal is to
56 engineer a system to achieve language comprehension with (at least) human-
57 level ability; for neuroscience, the goal is to understand the system that has
58 already done that: the human brain. Consequently, each field has developed
59 tools and insights that (perhaps with a bit of tweaking in implementation or
60 terminology) are mutually beneficial. Furthermore, solutions converged upon
61 by artificial systems may well serve as a useful hypothesis space for biological
62 systems, and vice versa.

63 2.1. Morphological segmentation: Identifying the building blocks

64 One of the earliest neural processes is morphological segmentation. The goal
65 is to locate the morphological constituents (roots, derivational and inflectional
66 affixes – defined fully below) within the written or spoken input, and link them
67 to a modality-specific representation (sometimes referred to as a form-based
68 “lexeme”² (Laudanna et al., 1992, Caramazza, 1997)). Evidence for morpho-
69 logical segmentation comes from both written and spoken language processing.
70 Putative anatomical locations for these processes are presented in Figure 1.

71 *Written word processing.* During reading, it appears that the brain segments
72 written words into morphemes based on an automatic morpho-orthographic
73 parser (Rastle et al. (2004), McCormick et al. (2008), Crepaldi et al. (2010),
74 Lavric et al. (2012), among others). Whenever both a valid stem (either free
75 or bound) and a valid suffix are present in the input, the parser is recruited
76 (e.g. *farm-er*, *post-age*, *explode-ion*) (Taft, 1979)). Here I use *valid* to mean
77 any morpheme that would be recognised as such by the grammar. Interestingly,
78 at this stage, the system is not yet sensitive to the semantic relatedness between
79 the stem and the complex form. This has been shown to lead to false parses of
80 mono-morphemic words like *corn-er* and *broth-er* (Rastle et al., 2004).

81 Visual morpheme decomposition has been associated with activity in the
82 fusiform gyrus using fMRI (Gold and Rastle, 2007), overlapping with the pu-
83 tative visual word form area (Cohen et al., 2002, McCandliss et al., 2003).
84 Corroborating evidence from MEG has also associated this area with morpho-
85 logical segmentation: Responses in posterior fusiform gyrus around 130 ms after
86 visual presentation are modulated by bi-gram and orthographic affix frequency
87 (Pammer et al., 2004, Simon et al., 2012, Gwilliams et al., 2016). This is con-
88 sistent with the research focused on orthographic processing, which associates
89 this area with the identification of recurring substrings (Dehaene et al., 2005,

²A lexeme relates to all inflected forms of a morpheme: play, plays, played, playing would all be grouped under the lexeme *play*.

90 Binder et al., 2006, Vinckier et al., 2007). Slightly more anterior along the
 91 fusiform, responses around 170 ms are modulated by morpheme-specific prop-
 92 erties such as stem frequency, affix frequency and the frequency with which
 93 those units combine (i.e. *transition probability*) (Solomyak and Marantz, 2010,
 94 Lewis et al., 2011, Fruchter and Marantz, 2015, Gwilliams and Marantz, 2018).
 95 Anterior fusiform gyrus is therefore associated with decomposing written input
 96 into morphemes.

97 *Spoken word processing.* Less research has been conducted on morphological
 98 segmentation of spoken language. Evidence from speech segmentation in general
 99 suggests that words and syllables are identified using statistical phonotactic
 100 regularitiess (Saffran et al., 1996), acoustic cues such as co-articulation and word
 101 stress (Cutler and Butterfield, 1992, Johnson and Jusczyk, 2001) and lexical
 102 information (Mattys et al., 2005). Similar kinds of statistical cues appear to
 103 be used for morpheme boundaries as well. In particular, there is sensitivity
 104 to the transition probability between spoken morphemes (Ettinger et al., 2014,
 105 Gwilliams and Marantz, 2015) in superior temporal gyrus (STG) at around
 106 200 ms after phoneme onset. These moments of low transition probability may

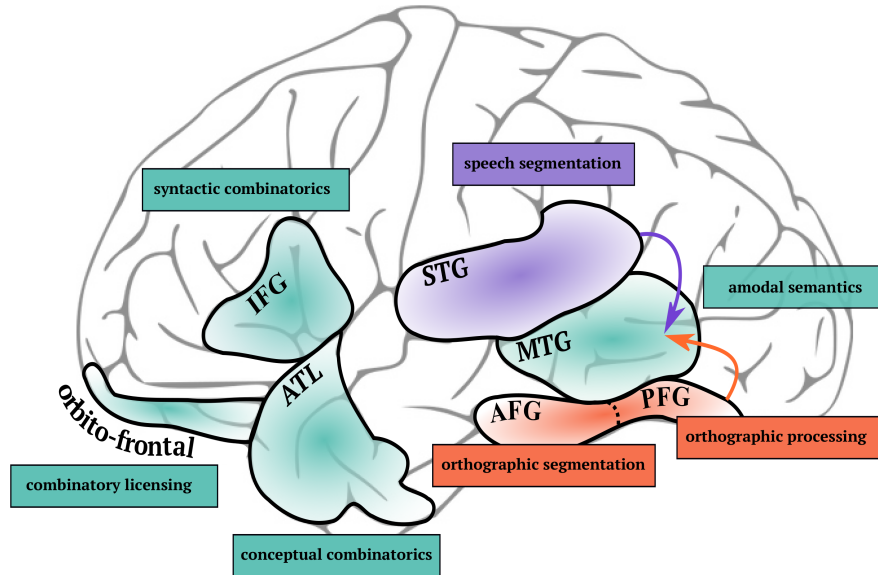


Figure 1: **Putative brain regions associated with different stages of morphological processing.** Orange colour refers to modality-specific written word processes. Purple colour to modality-specific spoken word processes. Turquoise refers to a-modal processes. PFG: posterior fusiform gyrus; AFG: anterior fusiform gyrus; STG: superior temporal gyrus; MTG: middle temporal gyrus; ATL: anterior temporal lobe; IFG: inferior frontal gyrus.

107 be used as boundary cues to bind phonological sequences into morphological
108 constituents.

109 *Links to NLP.* It is interesting to note that these neurophysiological findings are
110 echoed in the engineering solutions developed in natural language processing.
111 Some tools employ a storage “dictionary” of morphological constituents that
112 are compared to the input to derive units from the speech or text stream (Qiu
113 et al., 2014). This is similar to the stem+affix look-up approach of Taft (1979).
114 Other morphological segmentation tools such as *Morfessor* work by picking up
115 on statistical regularities in the input and maximising the likelihood of the parse
116 in a unsupervised manner (Creutz et al., 2007). This is related to sensitivity
117 to grapheme and phoneme transition probability as attested in the posterior
118 fusiform and superior temporal gyrus, respectively. Overall, both types of NLP
119 segmentation – dictionary lookup and statistical regularity – are attested in the
120 cognitive neuroscience literature as methods the brain uses for segmentation.

121 2.2. Lexical access: Figuring out what the blocks mean

122 Identifying the meaning of the segmented morphemes is often referred to as
123 “lexical access”. As shown at the base of Figure 2, this stage involves linking the
124 form-based morpheme to the relevant bundle of features. Each word consists
125 of at least three pieces: the root, (any number of) derivation(s) and inflection,
126 even if one of the pieces is not spelled out in the written or spoken language.
127 Depending on the type of morpheme being processed, the features are different.

128 2.2.1. Root access

129 Root morphemes are the smallest atomic elements that carry semantic fea-
130 tures. The root in *dogs* for example, is *dog*, which may have a feature for *brown*,
131 *fluffy*, *cute*, *small*, *mammal* and *barks*. In Figure 2, the collection of features is
132 visualised as a mathematical vector. Semantic vectors are frequently employed
133 in computational linguistics (e.g. Creutz and Lagus (2005), Snyder and Barzilay
134 (2008), Luong et al. (2013), Bojanowski et al. (2017)). They provide a powerful
135 way of representing meaning and obey simple geometric transformations (for
136 example, subtracting $\vec{m\grave{a}n}$ from $\vec{k\acute{i}ng}$ and adding $\vec{wo\breve{m}a}n$ results in a vector
137 that closely approximates $\vec{qu\acute{e}en}$ (Pennington et al., 2014)). In NLP, these vec-
138 tors are created based on the co-occurrence of words: capitalising on the fact
139 that words that mean something similar often occur in similar contexts. This is
140 highly consistent with the *Distributional Hypothesis* of semantics – a prevalent
141 linguistic theory of word meaning (Harris, 1954, Firth, 1957).

142 The middle temporal gyrus (MTG) has been implicated in semantic lexical
143 access in a number of processing models (Indefrey and Levelt, 2004, Hickok
144 and Poeppel, 2007, Friederici, 2012), along with the superior temporal sulcus
145 (Binder et al., 2000). A particular response component found in MEG, whose
146 neural source originates from MTG at around 350 ms after word onset, has
147 been associated specifically with access to the decomposed *root* of the whole
148 word (Pykkänen et al., 2004, 2006, Fiorentino and Poeppel, 2007, Solomyak
149 and Marantz, 2010, Fruchter and Marantz, 2015). Semantic vectors of the type

150 used by NLP have also been found to be correlated with a large network across
151 cortex (Huth et al., 2016).

152 2.2.2. Derivation access

153 Derivational morphology refers to a constituent that creates a new lexeme
154 from that to which it attaches. It typically does this by changing part of speech
155 (e.g. employ \rightarrow employment), by adding substantial non-grammatical meaning
156 (e.g. child \rightarrow childhood), or both (Anderson, 1985).

157 There are data from cross-modal priming studies indicating that derivational
158 suffixes can be primed from one word to another (darkNESS - happiNESS)
159 (Marslen-Wilson et al., 1996). This suggests that i) there is an amodal rep-
160 resentation that can be accessed and therefore primed during comprehension;
161 ii) the representation is somewhat stable in order to generalise across lexical
162 contexts. Furthermore, findings from fMRI link the processing of derived forms
163 with activity in the LIFG (Carota et al., 2016) – i.e. *Broca’s area*, which is
164 traditionally associated with syntactic processing, broadly construed. This re-
165 gion has also been associated with the processing of verbal argument structure
166 (Thompson et al., 2007), further implicating the LIFG in derivational morphol-
167 ogy.

168 Overall, however, the processing of derivation is not as clear as it is for roots
169 (Leminen et al., 2018). Consequently, there is little neuro-cognitive work to
170 draw upon regarding the specific features that a derivation contains. Given the
171 linguistic definition provided above, though, I propose that they consist of i)
172 morpho-syntactic features; ii) semantic features:

173 *Morpho-syntactic features.* Given the significant stability of word classes and
174 morpho-syntactic features cross-linguistically, it is possible that the derivation
175 contains a place-holder for all possible morpho-syntactic properties of the partic-
176 ular syntactic category (Cinque, 2006). This is very much in line with *categorical*
177 *structure* as proposed by Lieber (1992). For example, the morpheme *-ful*, which
178 derives an adjective from a noun, would contain adjectival morpho-syntactic
179 features such as *function*, *complementation*, *gradation*. The suffix *-ion* contains
180 nominal features such as *case*, *number*, *gender*. The suffix *-ify* contains verbal
181 features such as *tense*, *aspect*, *mood*.

182 Critically, the derivation only serves to specify which morpho-syntactic fea-
183 tures are of potential relevance. It does not actually contain the weights for
184 each dimension – that is the job of the inflection, as expanded upon below. In
185 this way, then, the derivation acts as a kind of co-ordinate frame: it determines
186 the word-class of the whole word by specifying the relevant syntactic dimensions
187 that it should be expressed within.

188 *Semantic features.* I propose that the derivation also contains semantic features
189 associated with the distributional use of the affix. This semantic feature would
190 be shared between *childhood*, *manhood* and *womanhood*, for example. Further-
191 more, there may also be semantic similarities within word classes more generally,
192 because words of the same syntactic category tend to occur in similar syntactic

193 contexts. For example, the semantic noun-y-ness associated with *mountain* may
 194 be shared with the noun-y-ness of *petrol*.

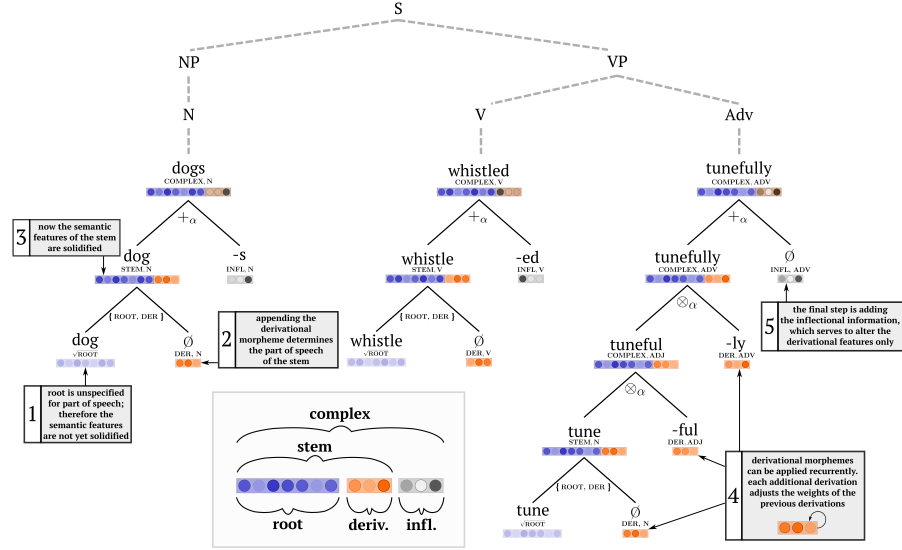


Figure 2: **Morpho-syntactic composition.** Detailing the morphological composition recruited during the processing of the sentence *dogs whistled tunelessly*. Purple vectors correspond to root and stem features; orange vectors to derivational morpho-syntactic features; grey-scale vectors to inflectional features. \emptyset : a morpheme with no phonological or orthographic realisation; $\{ \text{ROOT}, \text{DER} \}$: concatenation of vectors; \otimes : vector transformation through multiplication; $+$: addition; α : learnt combinatorial weight. I am assuming, in line with linguistic theories (Halle and Marantz, 1994, Harley and Noyer, 1999, Halle and Marantz, 2004), that the root is unspecified for word class (e.g. adjective, noun, verb).

195 2.2.3. Inflection access

196 Inflectional morphology invokes no change in word class or meaning of the
 197 root. Instead, it specifies the grammatical characteristics that are obliged by
 198 the given syntactic category (Anderson, 1985).

199 Similar to derivational morphology, although with more empirical support,
 200 inflectional morpho-syntactic properties appear to be processed in the left in-
 201 ferior frontal gyrus (LIFG) (Marslen-Wilson and Tyler, 2007, Whiting et al.,
 202 2014). This area is recruited for both overt and covert morphology (i.e. inflec-
 203 tions that are realised with a suffix (ten lamb + s) and those that are silent
 204 (ten sheep + \emptyset) (Sahin et al., 2009), which suggests that the same processing
 205 mechanisms are recruited even when the morphology is not realised phonetically
 206 or orthographically.

207 I propose that the inflectional morpheme serves to specify the value for each
 208 of the morpho-syntactic dimensions identified by the derivation. For example, if

the derivation recognises *number* as a relevant dimension for the stem, it is the inflection that specifies whether the word is singular or plural. If the derivation specifies a feature that is not applicable to the word being processed, such as *gender* for the English word *table*, then the inflection simply allocates a zero weight. This is consistent with Levelt et al. (1999)’s lexical access model of speech production.

2.3. Morphological combination: Putting the blocks together

In order to comprehend the meaning of the complex item, the system needs to put together the semantic and syntactic content of the constituents. This is referred to as the *recombination* stage of processing.

Concatenation to create the stem morpheme. The basic idea here is that the semantic properties of the root (purple vector in Figure 2, step 1) are concatenated with the morpho-syntactic properties of the derivation (orange vector, step 2). This derives a stem morpheme whose semantic features can be interpreted relative to its established word class.

Critically, the information encoded in the root vector is not interpretable until it is combined with the derivational morphology (Embick and Marantz, 2008), because only then is the stem specified for part of speech (step 3 in Figure 2). Even at this early stage, it easy to see that this combinatorial process has substantial consequences on meaning formation: contrast *(a) whistle* as a noun with *(to) whistle* as verb, for instance.

Multiplication at each derivation. After this initial stem-formation stage, any number of additional derivational operations can then be applied (step 4 in Figure 2). Each additional transformation involves adjusting which morpho-syntactic dimensions are relevant, as can be achieved with a multiplicative combinatorial rule (\otimes). This is mathematically equivalent to saying that the semantic vector of the stem is translated into a different vector space with each derivational step. For example, in Figure 2, the root *tune* is transformed into a nominal space at the first derivation; an adjectival space in the second, and adverbial space in the third.

Importantly, these transformations appear to have semantic consequences, not just syntactic ones. This links to the claim above that derivation contains the semantic features related to the word-class and affixal distribution of use. It is also possible that the process of multiplication has influences on the content of the stem morpheme, not just the previous derivation. As a result, this means that adding a nominalising suffix to a verbalising suffix does not preserve the meaning of the noun that was started off with. Behavioural studies have also shown that listeners are sensitive to the word class of the stem within complex forms (e.g. the verb *explode* in the nominalisation *explosion*) (Gwilliams et al., 2015), suggesting that the history of word classes is accessible during comprehension.

250 *Addition at the inflection.* The final stage involves combining the lexical struc-
 251 ture with the inflectional morpheme (grey-scale vector: step 5 in Figure 2).
 252 Here I have denoted the combinatorial operation as simple point-wise vector
 253 addition (+) between the morpho-syntactic features of the derivation (all of
 254 which are zero) and those of the inflection (non-zero). In this way, the inflection
 255 works to specify the weights of the derivational suffix, making explicit which
 256 morpho-syntactic properties are relevant and to what extent.

257 *NLP and neuro-imaging research.* Does this idea of vector combination work in
 258 practice? Work from NLP suggests that it could. Studies have used morpheme
 259 vector representations in a broad sense, though not strictly coding for semantic
 260 versus morpho-syntactic properties of the units (Creutz and Lagus, 2005, Luong
 261 et al., 2013, Snyder and Barzilay, 2008, Soricut and Och, 2015, Bojanowski et al.,
 262 2017). Even when using a simple composition rule such as addition between
 263 morpheme vectors, these composed vectors reasonably approximate semantic
 264 representations of morphologically complex whole words (Lazaridou et al., 2013,
 265 Cotterell and Schütze, 2018). This suggests that implementing even a very basic
 266 composition function could serve to generate complex lexical meaning.

267 Is there evidence for these kinds of combinatorial processes in the human
 268 brain? The majority of work on this combinatory stage of processing has fo-
 269 cused on comparing semantically valid to invalid morpheme combinations. For
 270 example, morphologically complex words like *farm-er* elicit a stronger EEG
 271 response at around 400-500 ms as compared to pseudo-complex words like *cor-*
 272 *ner* (Dominguez et al., 2004, Morris et al., 2007, 2008, Lavric et al., 2011,
 273 2012). MEG work has associated this with activity in the orbito-frontal cortex
 274 (Pylkkänen and McElree, 2007, Pylkkänen et al., 2009, Fruchter and Marantz,
 275 2015, Neophytou et al., 2018). This has been interpreted as reflecting a stage
 276 that assesses the compatibility between the composed complex representation
 277 and the predicted representation given the parts of the word.

278 *2.4. Feedback from the sentence structure*

279 Once the full sentence structure has been created, the system can use this
 280 structure for two purposes: i) *update* or strengthen the constituent represen-
 281 tations and composition rules; ii) *create* representations for novel morphemes.
 282 These ideas are illustrated in Figure 3.

283 *Update.* Once the sentence is built, feedback propagates back down the struc-
 284 ture to each morpheme representation and compositional rule. If the sentence
 285 structure has low semantic or syntactic validity, the feedback signal may update
 286 the constituent structure to improve validity for next time. Whereas if valid-
 287 ity is already high, the signal may simply strengthen the representations and
 288 combinatorial rules that are already in place. Thus, this feedback may be the
 289 mechanism by which the system learns that *farm-er* is morphologically com-
 290 plex and *corner* is not. This process could be implemented with something like
 291 back-propagation (Rumelhart et al., 1985).

292 *Create*. The proposal here is that the brain primarily conducts language pro-
 293 cessing via the atomic morphological units. Therefore it is critical that it en-
 294 sures full coverage over those units. When encountering a morpheme for the first
 295 time, the sentence structure can be used to generate the required constituent
 296 representations: First, the whole-word representation can be estimated from the
 297 sentence context (step 1 in Figure 3). Then, simple mathematical operations
 298 can be performed to interpolate atomic representations that may be missing
 299 from the lexicon (step 2).

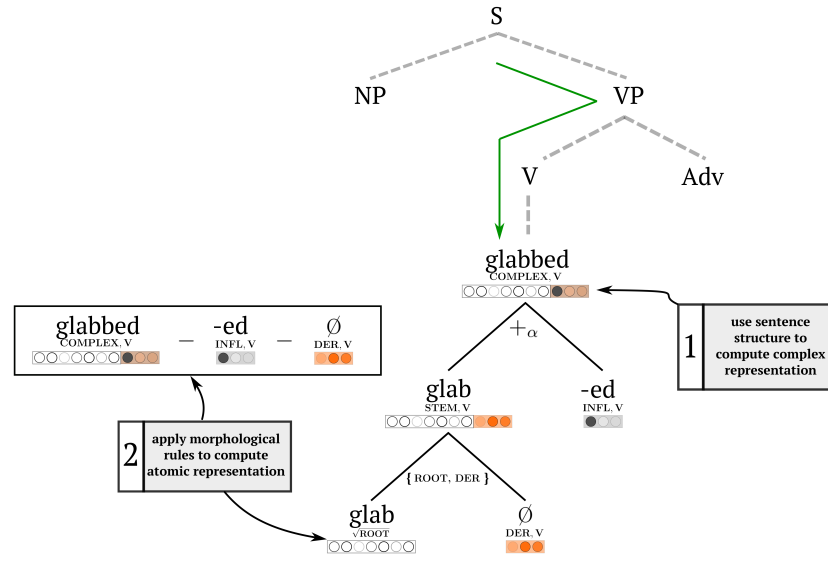


Figure 3: **Using sentence structure and morphological rules to generate representations.** The meaning of the novel word *glabbed* can be estimated using the meaning of the sentence structure (similar to jabberwocky sentences). From there, the meaning of all atomic elements are also generated, by performing simple mathematical operations on the known representations.

300 For example, as shown in Figure 3, if the system is encountering the word
 301 *glabbed* for the first time, but already has a representation of the past-tense
 302 inflectional morpheme *-ed*, then the whole-word representation can be extracted
 303 from the context³, and the representation of the root can be simply computed
 304 as:

³Note that when encountering a word for the first time, or trying to figure out whether a word is the correct one to select, a person will often embed that word into a sentence to assess its validity.

$$g\vec{lab} = g\vec{labbed} - \vec{ed} - \vec{\emptyset} \quad (1)$$

This interpolation process may serve to “initialise” the representation of a root vector. Then, at each subsequent use, the back-propagation-like process described above updates that representation.

While this process is most obviously recruited during language learning, the same mechanism is hypothesised to still be in effect in proficient speakers. Every time a listener is faced with a morphologically complex word, all of the atomic constituents of that word can be computed through an iterative subtraction of affixes. This makes the prediction that the system will hold representations of constituents that are never encountered in isolation: for example, of the root *excuse* from *excursion*. Recent evidence from MEG suggests that this is indeed the case (Gwilliams and Marantz, 2018).

Filling gaps in the lexicon through either interpolation of constituents, or combination into complex forms, is precisely the main advantage owed to morphological over word-based representations in NLP. The use of vector representations of morphemes provides better predictive power, especially for out-of-vocabulary words that do not exist in corpora (Creutz and Lagus, 2005, Luong et al., 2013, Snyder and Barzilay, 2008, Bojanowski et al., 2017).

Overall, this highlights that the systematicity between structure and meaning provides a powerful framework for generating missing semantic representations based on the syntactic (both lexical and sentential) situation alone. In this way, it is plausible that the language faculty *in general* is primed to associate syntactic information with particular semantic information. As discussed, this has clear advantages for language acquisition, as the process of meaning generation would be employed every time a new word is encountered.

3. Discussion

The goal of this paper is to offer a model of morphological composition that makes explicit i) the nature of morphological representations and ii) the operations performed on those representations. While the proposal is based as much as possible on extant literature, it also includes some untested, but testable, educated guesses. It would therefore be a fruitful avenue for future research to falsify the predictions of this model and update the assumptions accordingly.

For example, the compositional rule applied to morphemes is described as concatenation at the first derivation; multiplication at subsequent derivations and addition at the inflection. Further, the proposal suggests these operations must be performed in the order ascribed by the grammar. Whether this is indeed the type and order of neural operations needs to be tested, perhaps by testing whether a sequence of intermediate representations are encoded in neural activity before arriving at the final complex representation. It would also be informative to correlate the features of both the simple morpheme vectors and

345 the complex word vectors with neural activity to test whether composition in
346 the brain indeed obeys the mathematical operations outlined here.

347 Although this article has focused on morphological processing, it is possible
348 that these basic principles hold true across multiple units of language. The most
349 obvious analogy is between the syntactic operations used to generate phrasal
350 structures and those used to generate word structures. In line with linguistic
351 theory (Halle and Marantz, 1994, Harley and Noyer, 1999, Halle and Marantz,
352 2004), the current proposal makes no meaningful distinction between the two.
353 This is an intuitive idea. For instance, there is very little difference between the
354 composed meaning of *sort of blue* and *blueish*, even though one is made of a
355 phrasal structure and the other a lexical structure. Further, some languages may
356 choose to encode information using multiple words (e.g. *in the house*, English)
357 whereas others may use multiple morphemes (e.g. *extean*, Basque). That one
358 contains orthographic spaces and the other does not is quite arbitrary, and it is
359 not clear whether there are any meaningful processing differences (Moro et al.,
360 2001), above and beyond things like differences in unit size (Ullman, 2004).

361 4. Conclusion

362 Composition of morphological units provides insight into the infinite po-
363 tential of meaning expression, and the critical systematicity between syntactic
364 structure and semantic consequence. Here I have briefly reviewed research across
365 cognitive neuroscience, linguistics and natural language processing in order to
366 put forward a model of morphological processing in the human brain. I hope
367 that this serves as a useful overview, and highlights fruitful avenues for further
368 discovery.

369 Acknowledgements

370 This work was conducted through support from the Abu Dhabi Institute
371 (Grant G1001). I especially want to thank Alec Marantz for invaluable discus-
372 sion and comments on the manuscript. I also thank Linnaea Stockall, Samantha
373 Wray and Ryan Law for their very helpful suggestions.

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