English Semantic Feature Production Norms: An Extended Database of 4,436 Concepts

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14   Abstract

15   A limiting factor in understanding memory and language is often the availability of large

16   numbers of stimuli to use and explore in experimental studies. In this study, we expand on

17   three previous databases of concepts to over 4,000 words including nouns, verbs, adjectives,

18   and other parts of speech. Participants in the study were asked to provide lists of features

19   for each concept presented (a semantic feature production task), which were combined with

20   the previous research in this area. These feature lists for each concept were then coded into

21   their root word form and affixes (i.e., *cat* and *s* for *cats*) to explore the impact of word form

22   on semantic similarity measures, which are often calculated by comparing concept feature

23   lists (feature overlap). All concept features, coding, and calculated similarity information is

24   provided in a searchable database for easy access and utilization for future researchers when

25   designing experiments that use word stimuli. The final database of word pairs was combined

26   with the Semantic Priming Project to examine the relation of semantic similarity statistics

27   on semantic priming in tandem with other psycholinguistic variables.

28   *Keywords:* semantics, word norms, database, psycholinguistics

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Semantic features are the focus of a large area of research which tries to delineate the semantic representation of a concept. These features are key to models of semantic memory (i.e., memory for facts; Collins & Quillian, 1969; Collins & Loftus, 1975), and they have been used to create both feature based (Cree & McRae, 2003; Smith, Shoben, & Rips, 1974; Vigliocco, Vinson, Lewis, & Garrett, 2004) and distributional based models (Griffiths, Steyvers, & Tenenbaum, 2007; Jones & Mewhort, 2007; Riordan & Jones, 2011). Feature based models indicate that the degree of similarity between concepts is defined by their overlapping feature lists, while distributional based models posit that similarity is defined by the overlap between linguistic network or context. To create feature based similarity, participants were often asked to create lists of properties for categories of words. This property listing was a seminal task with corresponding norms that have been prevalent in the literature (Ashcraft, 1978; Rosch & Mervis, 1975; Toglia, 2009; Toglia & Battig, 1978). Feature production norms are created by soliciting participants to list properties or features of a target concept without focusing on category. These features are then compiled into feature sets that are thought to represent the memory representation of a particular concept, especially in early feature based models of memory (**???**; **???**; Collins & Loftus, 1975; Collins & Quillian, 1969). Previous work on semantic feature production norms in English includes databases by McRae, Cree, Seidenberg, and McNorgan (2005), Vinson and Vigliocco (2008), Buchanan, Holmes, Teasley, and Hutchison (2013), and Devereux, Tyler, Geertzen, and Randall (2014). McRae et al. (2005)'s feature production norms focused on 541 nouns, specifically living and nonliving objects. Vinson and Vigliocco (2008) expanded the stimuli set by contributing norms for 456 concepts that included both nouns and verbs. Buchanan et al. (2013) broadened to concepts other than nouns and verbs with 1808 concepts normed. The Devereux et al. (2014) norms included a replication of McRae et al. (2005)'s concepts with the addition of several hundren more concrete concepts. The current

55 paper represents over two thousand new concepts added to these previous projects and a

56 reanalysis of the original data.

57   For example, when queried on what features define a *cat*, participants may list *tail*,

58 *animal*, and *pet*. These features capture the most common types of descriptions: "is a" and

59 "has a". Additionally, feature descriptions may include uses, locations, behavior, and gender

60 (i.e., *actor* denotes both a person and gender). The goal of these norms is often to create a

61 set of high-probability features, as there can and will be many idiosyncratic features listed in

62 this task, to explore the nature of concept structure. In the classic view of category

63 structure, concepts have defining features or properties, while the probabilistic view suggests

64 that categories are fuzzy with concepts that are typical of a concept (Medin, 1989). These

65 norms have now been published in Italian (Montefinese, Ambrosini, Fairfield, & Mammarella,

66 2013; Reverberi, Capitani, & Laiacona, 2004), German (and Italian, Kremer & Baroni, 2011),

67 Portuguese (Stein & de Azevedo Gomes, 2009), Spanish (Vivas, Vivas, Comesaña, Coni, &

68 Vorano, 2017), and Dutch (Ruts et al., 2004), as well as for the blind (Lenci, Baroni,

69 Cazzolli, & Marotta, 2013).

70   Creation of these norms is vital to provide investigators with concepts that can be used

71 in future research. The concepts presented in the feature production norming task are usually

72 called *cues*, and the responses to the cue are called *features*. In a semantic priming task, the

73 concept paired with a cue (first word) is denoted as a *target* (second word). In a lexical

74 decision task, participants are shown cue words before a related or unrelated target word.

75 Their task is to decide if the target word is a word or nonword as quickly as possible. A

76 similar task, naming, involves reading the second target word aloud after viewing a related or

77 unrelated cue word. Semantic priming occurs when the target word is recognized (responded

78 to or read aloud) faster after the related cue word in comparison to the unrelated cue word

79 (Moss et al., 1995). The feature list data created from the production task can be used to

80 determine the strength of the relation between cue and target word, often by calculating the

81 feature overlap, or number of shared features between concepts (McRae et al., 2005). Both

82 the cue-feature lists and the cue-cue combinations (i.e., the relation between two cues in a

83 feature production dataset, which becomes a cue-target combination in the priming task) are

84 useful and important data for researchers in exploring various semantic based phenomena.

85   The feature category lists can provide insight into the probabilistic nature of language

86 and conceptual structure (Cree & McRae, 2003; McRae, Sa, & Seidenberg, 1997; Moss,

87 Tyler, & Devlin, 2002; Pexman, Holyk, & Monfils, 2003). Additionally, the feature

88 production norms can be used as the underlying data to create models of semantic priming

89 and cognition focusing on cue-target relation (Cree, McRae, & McNorgan, 1999; Rogers &

90 McClelland, 2004; Vigliocco et al., 2004). When using database norms to select for stimuli,

91 others have studied semantic word-picture interference (i.e., slower naming times when

92 distractor words are related category concepts in a picture naming task; Vieth, Mcmahon, &

93 Zubicaray, 2014), recognition memory (Montefinese, Zannino, & Ambrosini, 2015), and

94 semantic richness, which is a measure of shared defining features (Grondin, Lupker, &

95 McRae, 2009; Kounios et al., 2009; Yap, Lim, & Pexman, 2015; Yap & Pexman, 2016). The

96 Vinson and Vigliocco labs have shown the power of turning in-house data projects into a

97 larger norming set (Vinson & Vigliocco, 2008), as they published papers on aphasia (i.e., the

98 loss of understanding speech; Vinson & Vigliocco, 2002; Vinson, Vigliocco, Cappa, & Siri,

99 2003), meaning-syntactic differences (i.e., differences in naming times based on semantic or

100 syntactic similarity; Vigliocco, Vinson, Damian, & Levelt, 2002; Vigliocco, Vinson, & Siri,

101 2005), and representational models (Vigliocco et al., 2004).

102   However, it would be unwise to consider these norms as an exact representation of a

103 concept in memory (McRae et al., 2005). These norms represent salient features that

104 participants can recall, likely because saliency is considered special to our understanding of

105 concepts (Cree & McRae, 2003). Additionally, Barsalou (2003) suggested that participants

106 are likely creating a mental model of the concept based on experience and using that model

to create a feature property list. This model may represent a specific instance of a category (i.e., their pet dog), and feature lists will represent that particular memory. One potential solution to overcome saliency effects would be to solicit applicability ratings for features across multiple exemplars (i.e., specific members) of a category, as (**???**) have shown that this procedure provides reliable ratings across exemplars and provides more connections than the sparse representations that can occur when producing features.

Computational modeling of memory requires sufficiently large datasets to accurately portray semantic memory, therefore, the advantage of big data in psycholinguistics cannot be understated. There are many large corpora that could be used for exploring the structure of language and memory through frequency (see the SUBTLEX projects Brysbaert & New, 2009; New, Brysbaert, Veronis, & Pallier, 2007). Additionally, there are large lexicon projects that explore how the basic features of words affect semantic priming, such as orthographic neighborhood (words that are one letter different from the concept), length, and part of speech (Balota et al., 2007; Keuleers, Lacey, Rastle, & Brysbaert, 2012). In contrast to these basic linguistic features of words, other norming efforts have involved subjective ratings of concepts. Large databases of age of acquisition (i.e., rated age of learning the concept; Kuperman, Stadthagen-Gonzalez, & Brysbaert, 2012), concreteness (i.e., rating of how perceptible a concept is; Brysbaert, Warriner, & Kuperman, 2014), and valence (i.e., rating of emotion in a concept; Warriner, Kuperman, & Brysbaert, 2013) provide further avenues for understanding the impact these rated properties have on semantic memory. For example, age of acquisition and concreteness ratings have been shown to predict performance on recall tasks (Brysbaert et al., 2014; Dewhurst, Hitch, & Barry, 1998), while valence ratings are useful for gauging the effects of emotion on meaning (Warriner et al., 2013). These projects represent a small subset of the larger normed stimuli available (Buchanan, Valentine, & Maxwell, 2018), however, research is still limited by the overlap between these datasets. If a researcher wishes to control for lexical characteristics and subjective rating variables, the inclusion of each new variable to the study will further restrict the item pool for study.

134 Large, overlapping datasets are crucial for exploring the entire range of an effect, and to

135 ensure that the stimuli set is not the only contributing factor to the results of a study.

136   Therefore, the purpose of this study was to expand the number of cue and feature word

137 stimuli available, which additionally increases the possible cue-target pairings for studies

138 using word-pair stimuli (like semantic priming tasks). To accomplish these goals, we have

139 expanded our original semantic feature production norms (Buchanan et al., 2013) to include

140 all cues and targets from The Semantic Priming Project (Hutchison et al., 2013). The

141 existing norms were reprocessed along with these new norms to provide new feature coding

142 and affixes (i.e., word addition that modifies meaning, such as *pre* or *ing*) to explore the

143 impact of word form. Previously, Buchanan et al. (2013) illustrated convergent validity with

144 McRae et al. (2005) and Vinson and Vigliocco (2008) with a difference in approach to

145 processing feature production data. In McRae et al. (2005) and Vinson and Vigliocco (2008),

146 features were coded with complexity, matching "is a" and "has a" format that was first

147 found in Collins and Quillian (1969) and Collins and Loftus (1975) models. Buchanan et al.

148 (2013) took count based approach, wherein each feature is treated as a separate concept (i.e.

149 *four legs* would be treated as two features, rather than one complex feature). Both

150 approaches allow for the computation of similiarity by comparing feature lists for cue words,

151 however, the count based approach matches popular computational models, such as Latent

152 Semantic Analysis (Landauer & Dumais, 1997) and Hyperspace Analogue to Language (**???**).

153 These models treat each word in a document or text as a cue word and similarity is

154 computed by assessing a matrix of frequency counts between concepts and texts, which is

155 similar to comparing overlapping feature lists.

156   In the previous study, each feature was converted to common form if they denoted the

157 same concept (i.e., most features were translated to their root form). This process often

158 occurs to help capture the essential features without increasing the sparsity of the matrix

159 (i.e., the matrix only contains one representation for *beauty*, rather than several for all word

160 forms, thus lessening the number of empty cells in a cue-feature matrix). However, we

161 previously included a few exceptions to this coding system, such as *act* and *actor* when the

162 differences in features denoted a change of action (noun/verb) or gender or cue sets did not

163 overlap (i.e., features like *will* and *willing* did not have overlapping associated cues). These

164 exceptions were designed to capture how changes in morphology might be important cues to

165 word meaning, as hybrid models of word identification have outlined that morpheme

166 processing can be complex (**???**; **???**). Hybrid models include both a compositional view

167 (i.e., words are first broken down into their components *cat* and *s*; **???**; **???**) and a

168 full-listing view (i.e., each word form is represented completely separately, *cat* and *cats*) and

169 processing occurs as a race between each type of representation, **???**; **???**). Given these

170 models and sparsity considerations, we created a coding system to capture the feature word

171 meaning, in addition to morphology, to provide different levels of information about each

172 cue-feature combination. The entire dataset is available on our website

173 (http://wordnorms.com/) which has been revamped with a new interface and web

174 applications to easily find and select stimuli for future experiments. The data collection,

175 (re)processing, website, and finalized dataset are detailed below.

Method

Participants

178 Participants in the new stimuli set were recruited from Amazon's Mechanical Turk,

179 which is a large, diverse participant pool wherein users can complete surveys for small sums

180 of money (Buhrmester, Kwang, & Gosling, 2011). Answers can be screened for errors, and

181 incorrect or incomplete surveys can be rejected or discarded without payment. Each

182 participant was paid five cents for a survey, and they could complete multiple Human

183 Intelligence Tasks or HITS. Participants were required to be located in the United States

184 with a HIT approval rate of at least 80%, and no other special qualifications were required.

185 HITS would remain active until $n = 30$ valid survey answers were obtained. Table 1 includes

186 the sample sizes from the new study (Mechanical Turk 2), as well as the sample sizes from

187 the previous study, as described in Buchanan et al. (2013).

Materials

189   A main purpose of this second norming set was to expand the Buchanan et al. (2013)

190 norms to include all concepts from the Semantic Priming Project (Hutchison et al., 2013).

191 The original concept set was selected primarily from the Nelson, McEvoy, and Schreiber

192 (2004) database, with small overlaps in the McRae et al. (2005) and Vinson and Vigliocco

193 (2008) database sets for convergent validity. In the Semantic Priming Project, cue-target

194 pairs were shown to participants to examine naming (i.e., reading a concept aloud) and

195 lexical decision (i.e., responding if a presented string is a word or nonword) response latency

196 priming across related and unrelated pairs. The related pairs included first associate (most

197 common response to a cue, *sum-add*) and other associates (second or greater common

198 responses to cues, *safe-protect*) as their target words. The Buchanan et al. (2013)

199 publication of concepts included many of the cue words from the Semantic Priming Project,

200 while this project expanded to include unnormed cue words and all target words for all first

201 and other associate pairs. The addition of these concepts allowed for complete overlap

202 between the Semantic Priming Project and feature production norms. As mentioned earlier,

203 the McRae et al. (2005) norms consist primarily of nouns, the Vinson and Vigliocco (2008)

204 dataset includes nouns and verbs, while the Buchanan et al. (2013) included all word forms.

205   Concepts were labeled by part of speech using the English Lexicon Project (Balota et

206 al., 2007), the free association norms, and Google's define search when necessary. When

207 labeling these words, we used the most common part of speech to categorize concepts. This

208 choice was predominately for simplicity of categorization, however, the participants were

209 shown concepts without the suggestion of which sense to use for the word. Therefore,

210 multiple senses (i.e., *bat* is noun and a verb) are embedded into the feature production

211 norms, while the database is labeled with single parts of speech. The other parts of speech

212 can be found in the English Lexicon Project or multiple other databases. This dataset was

213 combined with McRae et al. (2005) and Vinson and Vigliocco (2008) feature production

214 norms, which resulted in a combined total of 4437 concepts. 70.4% of concepts were nouns,

215 14.9% adjectives, 12.4% verbs, and 2.3% were other forms of speech, such as adverbs and

216 conjunctions. The new concepts from this norming set only constituted: $n = 1916$ concepts,

217 72.0 nouns, 14.9% adjectives, 12.4% verbs, and 2.3% other parts of speech.

Procedure

219   Each HIT was kept to five concepts, and usual survey response times were between five

220 to seven minutes. Each HIT was open until thirty participants had successfully completed

221 the HIT and were paid the five cents for the HIT. HITS were usually rejected if they

222 included copied definitions from Wikipedia, "I don't know", or the participant wrote a

223 paragraph about the concept. These answers were discarded, as described below. The survey

224 instructions were copied from McRae et al. (2005)'s Appendix B, which were also used in

225 the previous publication of these norms. Because the McRae et al. (2005) data was collected

226 on paper, we modified these instructions slightly. The original lines to write in responses

227 were changed to an online text box response window. The detailed instructions additionally

228 no longer contained information about how a participant should only consider the noun of

229 the target concept, as the words in our study included multiple forms of speech and senses.

230 Participants were encouraged to list the properties or features of each concept in the

231 following areas: physical (looks, sounds, and feels), functional (uses), and categorical

232 (belongings). The exact instructions were as follows:

233   "We want to know how people read words for meaning. Please fill in features of the

234 word that you can think of. Examples of different types of features would be: how it looks,

sounds, smells, feels, or tastes; what it is made of; what it is used for; and where it comes from. Here is an example:

duck: is a bird, is an animal, waddles, flies, migrates, lays eggs, quacks, swims, has wings, has a beak, has webbed feet, has feathers, lives in ponds, lives in water, hunted by people, is edible

Complete this questionnaire reasonably quickly, but try to list at least a few properties for each word. Thank you very much for completing this questionnaire."

Participants signed up for the HITS through Amazon's Mechanical Turk website and completed the study within the Mechanical Turk framework. Approved HITs were compensated through the Mechanical Turk system. All answers were then combined into a larger dataset.

Data Processing

The entire dataset, at each processing stage described here, can be found at: https://osf.io/cjyzw/. On our OSF page, we have included a detailed processing guide on how concepts were (re)examined for this publication. This paper was written with *R* markdown (R Core Team, 2017) and *papaja* (Aust & Barth, 2018). The markdown document allows an interested reader to view the scripts that created the article in line with the written text. However, the processing of the text documents was performed on the raw files, and therefore, we have included the processing guide for transparency of each stage.

First, each concept was separated into an individual text file that is included as the "raw" data online. Each of these files was then spell checked and corrected when the participant answer was obviously a typo. As noted earlier, participants often tried to cut and paste Wikipedia or other online dictionary sources into the their answers to complete surveys

258 quickly with minimal effort. These entries were easily found because the formatting of the

259 webpage was included in their answer. For example, the Wikipedia entry for *zerba* includes

260 the phonetic spelling of the word, a set of paragraphs about zebras, a table of contents, and

261 then sectioned paragraphs matching that table of contents. To find this data, lab members

262 would open the raw text files that were compiled for each cue, look for these large blocks of

263 formatted text, and delete that information. Approximately 113 HITS were rejected because

264 of poor data, and 4524 HITS were paid. Therefore, we estimate approximately 2% of the

265 HITS included Wikipedia articles or other nonsense entries. Next, each concept was

266 processed for feature frequency. In this stage, the raw frequency counts of each cue-feature

267 combination were calculated and put together into one large file. Cue-cue combinations were

268 discarded, as participants might write "a zebra is a horse" when asked to define *zebra*.

269 English stop words such as *the, an, of* were then discarded, as well as terms that were often

270 used as part of a definition (*like, means, describes*).

271 We then created a "translated" column for each feature listed. This column indicated

272 the root word for each feature, and additional columns were added with the affixes that were

273 used in the original feature. For example, the original feature *cats* would be translated to *cat*

274 and *s*, wherein *cat* would be the translated feature and the *s* would be the affix code. The

275 translation was first started by using a Snowball type stemmer (**???**), written in Python by

276 a colleague of the first author. All original features and their roots from this process were

277 then put into an Excel document, which was reviewed by the first author for consistency and

278 concepts with affixes that were not stemmed. Usually the noun version of the feature would

279 be used for the translation or the most common part of speech for each feature.

280 At this stage, the data was reduced to cue-feature combinations that were listed by at

281 least 16% of participants (matching McRae et al. (2005)'s procedure) or were in the top five

282 features listed for that cue. This calculation was performed on the feature percent for the

283 root word (the *translated* column). For example, *beauty* may have been listed as *beauty,*

beautiful, beautifully, beautifulness, and this feature would have been listed four times in the dataset for the original cue (original feature in the *feature* column).

The sample size for the cue was added to this dataset, as the sample sizes varied across experiment time, as shown in Table 1. Therefore, instead of using raw feature frequency, we normalized each count into the percent of participants that included that feature with each cue. The *frequency_feature* column indicates the frequency of the original, unedited feature, while the *frequency_translated* includes all combinations of *beauty* into one overall feature. Because non-nouns can be more difficult to create a feature list for, we included the top five descriptors in addition to the 16% listed criteria, to ensure that each concept included at least five features. Table 2 indicates the average number of cue-feature pairs found for each data collection site/time point and part of speech for the cue word.

The parts of speech for the cue, original feature, and translated feature were merged with this file as described above. Table 3 depicts the pattern of feature responses for cue-feature part of speech combinations. This table includes the percent of features listed for each cue-feature part of speech combination (i.e., what is the percent of time that both the cue and feature were both adjectives) for the original feature (raw) and translated feature (root). Next, the average frequency percent was calculated along with their standard deviations. These columns indicate the percent that a cue-feature part of speech combination was listed across participants (i.e., what is the average percent of participants that listed an adjective feature for an adjective cue). These two types of calculation describe the likelihood of seeing part of speech combinations across the concepts, along with the likelihood of those cue-feature part of speech combinations across participants.

The top cue-feature combinations for the reprocessed and new data collection were then combined with the cue-feature combinations from McRae et al. (2005) and Vinson and Vigliocco (2008). We included all the cue-feature combinations listed in their supplemental files with the feature in the raw feature column. If features could be translated into root

words with affixes, the same procedure as described above was applied. The final file then included columns for the original dataset, cue, feature, translated feature, frequency of the original feature, frequency of the translated feature, sample size, and frequency percentages for the original and translated feature. The cue-feature file includes 69284 cue-raw feature combinations, where 48925 are from our dataset, and 24449 of which are cue-translated feature combinations. Statistics in Tables 2 and 3 only include information from the reprocessed Buchanan et al. (2013) norms and the new cues collected for this project.

The final data processing step was to code affixes found on the original features. Multiple affix codes were often needed for features, as *beautifully* would have been translated to *beauty*, *ful*, and *ly* (the *a1, a2, a3* columns). The research team searched lists of affixes online and collectively discussed how to code each affix, and the complete coding system can be found online in our OSF files. If an affix coding was unclear, the root and affix word were discussed in a lab meeting. Table 4 displays the list of affix types, common examples for each type of affix, and the percent of affixes that fell into each category. The percent values are calculated on the overall affix list, as feature words could have up to three different affixes. Generally, affixes were tagged in a one-to-one match, however, special care was taken with numbers and verb tenses, and the lead author checked these categories after lab member coding. Features like cat*s* would be coded as a number affix, while features like walk*s* would be coded as a third person verb.

In the final words file found online, we additionally added forward strength (FSG) and backward strength (BSG) for investigation into association overlap (Nelson et al., 2004). Forward strength indicates the number of times a target word was listed in response to a cue word in a free association task, which simply asks participants to name the first word that comes to mind when presented with a cue word. Backward strength is the number of times a cue word was listed with a target word, as free association is directional (i.e., the number of times *cheese* is listed in response to *cheddar* is not the same as the number of times that

cheddar is listed in response to *cheese*). The last few columns indicate the word list a

concept was originally normed in to allow for matching to the original raw files on the OSF

page, along with the code for each school and time point of collection.

Both forms of the feature are provided for flexibility in calculating overlap by using the

original feature (raw), the translated feature (root), and the affix overlap by code (affix).

Cosine values were calculated for each of these feature sets by using the following formula:

$$\frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

This formula is similar to a dot-product correlation, where A_i and B_i indicate the

overlapping feature frequency (normalized, therefore, the percent) between cue A and cue B.

The i subscript denotes the current cue, and when features match, the frequencies are

multiplied together and summed across all matches (Σ). For the denominator, the feature

frequency is first squared and summed from i to n features for cue A and B. The square root

of these summation values is then multiplied together. In essence, the numerator calculates

the overlap of feature frequency for matching features, while the denominator accounts for

the entire feature frequency set for each cue. Cosine values range from 0 (no overlapping

features) to 1 (complete overlapping features). With over four thousand cue words, just

under twenty million cue-cue cosine combinations can be calculated. In the datasets

presented online, we only included cue-cue combinations with a feature overlap of at least

two features, in order to reduce the large quantity of zero and very low cosine values. This

procedure additionally allowed for online presentation of the data, as millions of cosines were

not feasible for our server. The complete feature list, along with our code to calculate cosine,

can be used to obtain values not presented in our data if desired.

Website

In addition to our OSF page, we present a revamped website for this data at
http://www.wordnorms.com/. The single words page includes information about each of the
cue words including cue set size, concreteness, word frequency from multiple sources, length,
full part of speech, orthographic/phonographic neighborhood, and number of phonemes,
syllables, and morphemes. These values were taken from Nelson et al. (2004), Balota et al.
(2007), and Brysbaert and New (2009). A definition of each of these variables is provided
along with the minimum, maximum, mean, and standard deviation of numeric values. The
table is programmed using Shiny apps (Chang, Cheng, Allaire, Xie, & McPherson, 2017).
Shiny is an *R* package that allows the creation of dynamic graphical user interfaces for
interactive web applications. The advantage to using Shiny applications is data manipulation
and visualization with the additional bonus of up to date statistics for provided data (i.e., as
typos are fixed or data is updated, the web app will display the most recent calculations). In
addition to the variable table, users can search and save filtered output using our Shiny
search app. With this app, you can filter for specific variable ranges and save the output in a
csv or Excel file. The complete data is also provided for download.

On the word pairs page, all information about word-pair statistics can be found. A
second variable table is provided with semantic and associative statistics. This dataset
includes the cue and target words from this project (cue-cue combinations), the root, raw,
and affix cosines described above, as well as the original Buchanan et al. (2013) cosines.
Additional semantic information includes Latent Semantic Analysis (LSA; Landauer &
Dumais, 1997) and JCN (JCN stands for Jiang-Conrath, see explanation below; Jiang &
Conrath, 1997) values provided in the Maki, McKinley, and Thompson (2004) norms, along
with forward strength and backward strength (FSG; BSG) from the Nelson et al. (2004)
norms for association. The definitions, minimum, maximum, mean, and standard deviations
of these values are provided in the app. Again, the search app includes all of these stimuli for

cue-cue combinations with two or more features in common, where you can filter this data for experimental stimuli creation. The separation of single and word-pair data (as well as cosine calculation reduction to cues with two features in common) was practical, as the applications run slowly as a factor of the number of rows and columns of data. On each page, we link the data, applications, and source code so that others may use and manipulate our work depending on their data creation or visualization goals.

Results

An examination of the results of the cue-feature lists indicated that the new data collected was similar to the previous semantic feature production norms. As shown in Table 2, the new Mechanical Turk data showed roughly the same number of listed features for each cue concept, usually between five to seven features. These numbers represent, for each cue and part of speech, the average number of distinct cue-feature pairs provided by participants after processing. Table 3 portrayed that adjective cues generally included other adjectives or nouns as features, while noun cues were predominately described by other nouns. Verb cues included a large feature list of nouns and other verbs, followed by adjectives and other word forms. Lastly, the other cue types generally elicited nouns and verbs. Frequency percentages were generally between seven and twenty percent when examining the raw words. These words included multiple forms, as the percent increased to around thirty percent when features were translated into their root words. Indeed, nearly half of the 48925 cue-feature pairs were repeated, as 24449 cue-feature pairs were unique when examining translated features. Generally, because of the translation process, word forms shifted towards nouns and verbs and away from adjectives because adjectives are often formed by adding an affix to a noun or verb.

36030 affix values were found, which arose from 4407 of the 4436 cue concepts. 33052 first affixes were found, with 2832 second place affixes, and 146 third place affixes. Table 4

₄₀₈ shows the distribution of these affix values. Generally, numbers were the largest category of

₄₀₉ affixes demonstrating that participants often indicated the quantity of the feature when

₄₁₀ describing the cue word. The second largest affix category was characteristics which denoted

₄₁₁ the switch to or from a noun form of the feature word (i.e., *angry* to *anger*). Verb tenses

₄₁₂ (past tense, present participle, and third person) comprised a large set of affixes indicating

₄₁₃ the type of concept or when a concept might be doing an action for a cue. Persons and

₄₁₄ objects affixes were used about 7% of the time on features to explain cues, while actions and

₄₁₅ processes were added to the feature about 8% of the time.

Divergent Validity

₄₁₇   When collecting semantic feature production norms, there can be a concern that the

₄₁₈ information produced will simply mimic the free association norms, and thus, be a more of

₄₁₉ representation of association (context) rather than semanticity (meaning). Association and

₄₂₀ semanticity do overlap, however, the variables used to represent these concepts have been

₄₂₁ shown to tap different underlying constructs (Maki & Buchanan, 2008). Therefore, it is

₄₂₂ important to show that, while some overlap is expected, the semantic feature production

₄₂₃ norms provide useful, separate information from the free association norms. Table 5 portrays

₄₂₄ the overlap with the Nelson et al. (2004) norms. The percent of time a cue-feature

₄₂₅ combination was present in the free association norms was calculated, along with the average

₄₂₆ forward strength for those overlapping pairs. First, these values were calculated on the

₄₂₇ complete dataset with the McRae et al. (2005) and Vinson and Vigliocco (2008) norms, as we

₄₂₈ are presenting them as a combined dataset, on the translated cue-feature set only. Because

₄₂₉ we used the translated cue-feature set, repeated instances of cue-features would occur (i.e.,

₄₃₀ the original *abandon-leave* and *abandon-leaving* becomes two lines when only using translated

₄₃₁ *abandon-leave*), and only the unique set was considered. Second, we calculated these values

₄₃₂ on each dataset separately, as well as the 26 cues that overlapped in all three datasets.

433   The overall overlap between the database cue-feature sets and the free association

434   cue-target sets was approximately 37%, ranging from 32% for verbs and nearly 52% for

435   adjectives. Similar to our previous results, the range of the forward strength was large (.01 -

436   .94), however, the average forward strength was low for overlapping pairs, $M = .11$ ($SD =$

437   .14). These results indicated that while it will always be difficult to separate association and

438   meaning, the dataset presented here represents a low association when examining

439   overlapping values, and more than 60% of the data is completely separate from the free

440   association norms. The limitation to this finding is the removal of idiosyncratic responses

441   from the Nelson et al. (2004) norms, but even if these were to be included in some form, the

442   average forward strength would still be quite low when comparing cue-feature lists to

443   cue-target lists. In examining these values by dataset, it appears that the new norms have

444   the highest overlap with the Nelson et al. (2004) data, while the average, standard deviation,

445   minimum, and maximum values were roughly similar for each dataset and the overlapping

446   cues. This effect is likely driven by the inclusion of adjectives and other forms of speech,

447   which show higher overlaps than nouns and verbs, which represent the cues present in

448   McRae et al. (2005) and Vinson and Vigliocco (2008).

449   **Convergent Validity**

450   To examine the validity of cosine values, we calculated the average cosine score

451   between the new processing of the data for each of the three feature production norms used

452   in this project. Overlapping cues in each of three database sets were found ($n = 188$), and

453   the average cosine between their feature sets was examined. Buchanan et al. (2013) and the

454   new dataset are listed with the subscript B, while McRae et al. (2005) is referred to with M

455   and V for Vinson and Vigliocco (2008). For root cosine values, we found high overlap

456   between all three datasets: $M_{BM} = .67$ ($SD = .14$), $M_{BV} = .66$ ($SD = .18$), and $M_{MV} = .72$

457   ($SD = .11$). The raw cosine values also correlated, even though the McRae et al. (2005) and

458 Vinson and Vigliocco (2008) datasets were already mostly preprocessed for word stems:

459 $M_{BM} = .55$ ($SD = .15$), $M_{BV} = .54$ ($SD = .20$), and $M_{MV} = .45$ ($SD = .19$). Last, the affix

460 cosines overlapped similarly between Buchanan et al. (2013) and McRae et al. (2005)

461 datasets, $M_{BM} = .43$ ($SD = .29$), but did not overlap with the Vinson and Vigliocco (2008)

462 datasets: $M_{BV} = .04$ ($SD = .14$), and $M_{MV} = .09$ ($SD = .19$), likely due to Vinson and

463 Vigliocco (2008) dataset preprocessing.

464   The correlation between root, raw, affix, previously found cosine, Latent Semantic

465 Analysis score (LSA), and Jiang-Conrath semantic distance (JCN) were calculated to

466 examine convergent validity. LSA is one of the most well-known semantic memory models

467 (**???**; Landauer & Dumais, 1997), wherein a large text corpus (i.e., many texts) is used to

468 create a word by document (i.e., each text) matrix. From this matrix, words are weighted

469 relative to their frequency, and singular value decomposition is then used to select only the

470 largest semantic components. This process creates a word space that can then be used to

471 calculate the relation between two cues by examining the patterns of their occurrence across

472 documents, usually cosine or correlation. JCN is calculated from an online dictionary

473 (WordNet, Fellbaum & Felbaum, 1998), by measuring the semantic distance between

474 concepts in a hierarchical structure. JCN is backwards coded, as zero values indicate close

475 semantic neighbors (low dictionary distance) and high values indicate low semantic relation.

476 These two measures were selected for convergent validity because they are well-cited

477 measures of semanticity.

478   As shown in Table 6, the intercorrelations between the cosine measures (root, raw,

479 affix) are high, especially between our previous work and this dataset. The small negative

480 correlations between JCN and cosine measures replicated previous findings (Buchanan et al.,

481 2013). LSA values showed small positive correlations with cosine values, indicating some

482 overlap with thematic information and semantic feature overlap (Maki & Buchanan, 2008).

483 These correlations were slightly different than our previous publication, likely because here

we restricted this cosine set to values with at least two features in common. LSA and JCN

correlations were lower than LSA-cosine and JCN-cosine, but these values indicated that

themes and dictionary distance were similarly related to feature overlap.

Relation to Semantic Priming

As a second examination of convergent validity, the correlation between values

calculated from these norms and the *Z*-priming values from the Semantic Priming Project

were examined. The Semantic Priming Project includes lexical decision and naming response

latencies for priming at 200 and 1200 ms stimulus onset asynchronies (SOA). In these

experiments, participants were shown cue-target words that were either the first associate of

a concept or an other associate (second response or higher in the Nelson et al. (2004) norms)

with the delay between the cue and target matching either 200 or 1200 ms (SOA). The

response latency of the target word in the related condition (either first or other associate)

was subtracted from the response latency in the unrelated condition to create a priming

response latency. Therefore, each target item received four (two SOAs by two tasks: lexical

decision or naming) priming times. We selected the *Z*-scored priming from the dataset to

correlate with our data, as Hutchison et al. (2013) that the *Z*-scored data more accurately

captures priming controlled for individual differences in reaction times.

In addition to root, raw, and affix cosine, we additionally calculated feature set size for

the cue and target of the primed pairs. Feature set size is the number of features listed by

participants when creating the norms for that concept. Because of the nature of our norms,

we calculated both feature set size for the raw, untranslated features, as well as the

translated features. The average feature set sizes for our dataset can be found in Table 2.

The last variable included was cosine set size which was defined as the number of other

concepts each cue or target was nonzero paired with in the cosine values. Feature set size

indicates the number of features listed for each cue or target, while cosine set size indicates

509 the number of other semantically related concepts for each cue or target. Feature and cue set

510 size are often called semantic richness, representing the variability or extent of associated

511 information for a cue (**???**; **???**; **???**). Several studies have showed the positive effects of

512 semantic richness on semantic tasks based on task demand (**???**; **???**; **???**; **???**), and thus,

513 they were included as important variables to examine.

514   Tables 7 and 8 display the correlations between the new semantic variables described

515 above, as well as forward strength, backward strength, Latent Semantic Analysis score, and

516 Jiang-Conrath semantic distance for reference. Only cue-target pairs with complete values

517 were included in this analysis to allow for comparison between correlations. For lexical

518 decision priming, we found small correlations between the root and raw cosine values and

519 priming, with the largest for first associates in the 200 ms condition. The correlations

520 decreased for the 1200 ms condition and the other associate SOAs. These two variables are

521 highly correlated, therefore, it is not surprising that they have similar correlations with

522 priming. Affix cosine also was slightly related to priming, especially for first associates in the

523 200 ms condition. Most of the cue and feature set sizes were not related to priming, showing

524 correlations close to zero in most instances. Cue set size for the cue word was somewhat

525 related to 200 ms priming, along with raw cue feature set size. These correlations are small,

526 but they are comparable or greater than the correlations for association and other measures

527 of semantic or thematic relatedness. For naming, the results are less consistent. Cosine

528 values are related to 1200 ms naming in first associates, and none of the feature or cue set

529 sizes showed any relationship with priming. Again, we see that many of the other associative

530 and semantic variables correspondingly do not correlate with priming. In both naming and

531 lexical decision priming, backward strength has a small but consistent relationship with

532 priming, which may indicate the processing of the target back to the cue. Latent Semantic

533 Analysis score was also a small predictor of priming across conditions.

₅₃₄   **Discussion**

₅₃₅   This research project focused on expanding the availability of English semantic feature

₅₃₆ overlap norms, in an effort to provide more coverage of concepts that occur in other large

₅₃₇ database projects like the Semantic Priming and English Lexicon Projects. The number and

₅₃₈ breadth of linguistic variables and normed databases has increased over the years, however,

₅₃₉ researchers can still be limited by the concept overlap between them. Projects like the Small

₅₄₀ World of Words provide newly expanded datasets for association norms, and our work helps

₅₄₁ fill the voids for corresponding semantic norms. To provide the largest dataset of similar

₅₄₂ data, we combined the newly collected data with previous work by using Buchanan et al.

₅₄₃ (2013), McRae et al. (2005), and Vinson and Vigliocco (2008) together. These norms were

₅₄₄ reprocessed from previous work to explore the impact of feature coding for feature overlap.

₅₄₅ As shown in the correlation between root and raw cosines, the parsing of words to root form

₅₄₆ created very similar results across other variables. This finding does not imply that these

₅₄₇ cosine values are the same, as root cosines were larger than their corresponding raw cosine.

₅₄₈ It does, however, imply that the cue-feature coding can produce similar results in raw or

₅₄₉ translated format. Because the correlation between the current paper's cosine values and the

₅₅₀ previous cosine values was nearly 1, we would suggest using the new values, simply for the

₅₅₁ increase in dataset size.

₅₅₂   Of particular interest was the information that is often lost when translating raw

₅₅₃ features back to a root word. One surprising result in this study was the sheer number of

₅₅₄ affixes present on each cue word. With these values, we believe we have captured some of the

₅₅₅ nuance that is often discarded in this type of research. Affix cosines were less related to their

₅₅₆ feature root and raw counterparts, but also showed small correlations with semantic priming.

₅₅₇ Potentially, affix overlap can be used to add small, but meaningful predictive value to related

₅₅₈ semantic phenomena. Further investigation into the compound prediction of these variables

₅₅₉ is warranted to fully explore how these, and other lexical variables, may be used to

560 understand semantic priming. An examination of the cosine values from the Semantic

561 Priming Project cue-target set indicates that these values were low, with many zeros (i.e., no

562 feature overlap between cues and targets). This restriction of range of the cosine relatedness

563 could explain the small correlations with priming because the semantic priming was variable,

564 but the cosine values were not.

565 We encourage readers to use the corresponding website associated with these norms to

566 download the data, explore the Shiny apps, and use the options provided for controlled

567 experimental stimuli creation. We previously documented the limitations of feature

568 production norms that rely on on single word instances as their features (i.e., *four* and *legs*),

569 rather than combined phrase sets. One limitation, potentially, is the inability to create fine

570 distinctions between cues; however, the small feature set sizes imply that the granulation of

571 features is large, since many distinguishing features are often never listed in these tasks. For

572 instance, *dogs* are living creatures, but *has lungs* or *has skin* would usually not be listed

573 during a feature production task, and thus, feature sets should not be considered a complete

574 snapshot of mental representation (Rogers & McClelland, 2004). The previous data and

575 other norms were purposely combined in the recoded format, so that researchers could use

576 the entire set of available norms which increases comparability across datasets. Given the

577 strong correlation between databases, we suspect that using single word features does not

578 reduce their reliability and validity.

579 One other important limitation of the instructions in this study is that multiple senses

580 of concepts were not distinguished. We did not wish to prime participants for specific senses

581 to capture the features for multiple senses of a concept, however, this procedure could lead

582 to lower cosine values for concepts that might intuitively seem very related. The feature

583 production lists could be used to sort senses and recalculate overlap values, but it is likely

584 that feature information is correspondingly mixed or sorted into small sublists in memory as

585 well. The addition of the coded affix information may help capture some of those sense

differences, as well as the some of the spatial and relational features that are not

traditionally captured by simple feature production. For example, by understanding the

numbers or actors affixes, we may gain more information about semanticity that is often

regarded as something to disregard in data processing.

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Table 1

Sample Size and Concept Norming Size for Each Data Collection Location/Time Point

Institution	Total Participants	Concepts	Mean N
University of Mississippi	749	658	67.8
Missouri State University	1420	720	71.4
Montana State University	127	120	63.5
Mechanical Turk 1	571	310	60
Mechanical Turk 2	198	1914	30

Table 2

Average (SD) Cue-Feature Pairs by Location/Time Point

Institution	Adjective	Noun	Verb	Other	Total
University of Mississippi	5.57 (1.53)	7.35 (4.05)	5.33 (.87)	6.01 (2.11)	6.71 (3.44)
Missouri State University	5.74 (1.56)	6.85 (2.82)	6.67 (2.08)	7.45 (5.35)	6.65 (2.92)
Montana State University	5.81 (1.74)	7.25 (3.35)	5.59 (1.13)	5.76 (1.74)	6.69 (2.93)
Mechanical Turk 1	6.27 (2.28)	7.74 (4.34)	5.77 (1.17)	5.57 (1.40)	7.14 (3.79)
Mechanical Turk 2	5.76 (1.36)	6.62 (1.85)	5.92 (1.38)	5.78 (1.17)	6.38 (1.75)
Total	5.78 (1.61)	6.94 (2.88)	5.67 (1.18)	5.84 (1.71)	6.57 (2.60)

Table 3

Percent and Average Percent of Frequency for Cue-Feature Part of Speech

Combinations

Cue Type	Feature Type	% Raw	% Root	*M* Freq. Raw	*M* Freq. Root
Adjective	Adjective	38.09	29.74	17.84 (16.47)	30.02 (18.83)
	Noun	40.02	46.74	13.14 (14.96)	29.71 (19.94)
	Verb	17.69	20.72	8.51 (9.78)	26.88 (17.27)
	Other	4.20	2.80	15.17 (15.64)	28.04 (15.54)
Noun	Adjective	16.56	12.07	15.55 (15.17)	31.20 (18.17)
	Noun	60.85	62.67	17.21 (17.01)	33.26 (20.05)
	Verb	20.80	23.68	8.88 (9.73)	31.01 (17.87)
	Other	1.79	1.58	17.06 (15.29)	28.87 (17.14)
Verb	Adjective	15.16	12.27	13.95 (13.98)	30.03 (18.28)
	Noun	42.92	44.35	14.59 (14.92)	29.59 (18.90)
	Verb	36.92	39.72	12.75 (14.85)	30.43 (19.54)
	Other	5.00	3.66	19.16 (15.95)	25.59 (19.54)
Other	Adjective	20.80	20.32	16.61 (17.37)	31.66 (19.51)
	Noun	42.74	39.03	16.77 (19.41)	37.28 (25.94)
	Verb	19.66	23.93	7.18 (7.57)	26.14 (19.38)
	Other	16.81	16.71	22.72 (16.69)	30.70 (18.48)
Total	Adjective	19.74	14.93	16.12 (15.57)	30.75 (18.37)
	Noun	55.41	57.81	16.55 (16.74)	32.58 (20.09)
	Verb	22.02	24.95	9.50 (10.91)	30.29 (18.24)
	Other	2.82	2.31	17.76 (15.83)	28.45 (16.83)

Note. Raw words indicate original feature listed, while root words indicated

translated feature. These data are only from the current project.

Table 4

Example of Affix Coding and Percent of Affixes Found

Affix Type	Example	Percent
Actions/Processes	ion, ment, ble, ate, ize	8.21
Characteristic	y, ous, nt, ful, ive, wise	22.72
Location	under, sub, mid, inter	0.44
Magnitude	er, est, over, super, extra	1.31
Not	less, dis, un, non, in , im, ab	2.76
Number	s, uni, bi, tri, semi	28.31
Opposites/Wrong	mis, anti, de	0.13
Past Tense	ed	8.03
Person/Object	er, or, men, person, ess, ist	7.23
Present Participle	ing	14.03
Slang	bros, bike, bbq, diff, h2o	0.12
Third Person	s	6.16
Time	fore, pre, post, re	0.54

Table 5

Percent and Mean Overlap to the Free Association Norms

	% Overlap	*M* FSG	*SD* FSG	Min	Max
Adjective	51.86	.12	.15	.01	.94
Noun	36.48	.11	.14	.01	.91
Verb	32.15	.11	.13	.01	.94
Other	44.44	.13	.18	.01	.88
Total	37.47	.11	.14	.01	.94
All Buchanan cues	52.12	.11	.14	.01	.94
McRae et al. cues	23.50	.10	.14	.01	.91
Vinson & Vigliocco cues	15.19	.09	.13	.01	.88
Overlapping Cues	27.26	.09	.14	.01	.88

Note. Overlap was defined as the percent of cue-feature combinations from our feature list included in the Nelson et al. (2004) norms. FSG: Forward strength indicating the number of times a target was elicited after seeing a cue word.

Table 6

Correlations and 95% CI between Semantic and Associative Variables

	Root	Raw	Affix	PCOS	JCN	LSA	FSG	BSG
Root	1	208515	208515	83762	5617	5590	6753	6685
Raw	.93 [.93, .93]	1	208515	83762	5617	5590	6753	6685
Affix	.50 [.50, .50]	.53 [.53, .54]	1	83762	5617	5590	6753	6685
Previous COS	.94 [.94, .94]	.91 [.91, .91]	.49 [.48, .49]	1	2762	2759	3280	3243
JCN	-.18 [-.20, -.15]	-.22 [-.25, -.20]	-.17 [-.20, -.15]	-.22 [-.26, -.19]	1	5590	5617	5617
LSA	.18 [.16, .21]	.15 [.12, .18]	.10 [.07, .13]	.21 [.18, .25]	-.06 [-.08, -.03]	1	5590	5590
FSG	.06 [.04, .08]	.04 [.01, .06]	.08 [.05, .10]	.10 [.06, .13]	-.15 [-.18, -.13]	.24 [.22, .27]	1	6685
BSG	.14 [.12, .16]	.15 [.13, 17]	.17 [.14, .19]	.18 [.15, .22]	-.18 [-.21, -.16]	.26 [.23, .28]	.31 [.29, .33]	1

Note. Root, raw, and affix cosine values are from the current reprocessed dataset. PCOS indicates the cosine values in the original Buchanan et al. (2013) dataset. JCN: Jiang-Conrath semantic distance, LSA: Latent Semantic Analysis score, FSG: Forward Strength, BSG: Backward Strength. Sample sizes for each correlation are presented in the top half of the table.

Table 7

Lexical Decision Response Latencies' Correlation and 95% CI with Semantic and Associative Variables

Variable	First 200	First 1200	Other 200	Other 1200
Root Cosine	.13 [.07, .18]	.07 [.02, .13]	.09 [.03, .14]	.09 [.03, .14]
Raw Cosine	.12 [.06, .17]	.07 [.01, .12]	.09 [.04, .15]	.07 [.01, .12]
Affix Cosine	.09 [.03, .14]	.08 [.02, .13]	.06 [.00, .11]	.04 [-.01, .10]
Target Root FSS	.01 [-.04, .06]	-.01 [-.07, .04]	-.03 [-.09, .02]	-.03 [-.08, .03]
Target Raw FSS	-.00 [-.06, .05]	-.02 [-.08, .03]	-.03 [-.08, .03]	-.02 [-.08, .03]
Target CSS	.02 [-.04, .07]	.01 [-.04, .07]	-.05 [-.10, .01]	.02 [-.04, .07]
Cue Root FSS	.04 [-.02, .09]	-.02 [-.07, .04]	.03 [-.02, .09]	.03 [-.02, .09]
Cue Raw FSS	.05 [-.01, .10]	-.02 [-.08, .03]	.01 [-.05, .06]	.01 [-.04, .07]
Cue CSS	.05 [.00, .11]	-.00 [-.06, .05]	.06 [.01, .12]	.01 [-.05, .06]
Forward Strength	.04 [-.01, .10]	.11 [.06, .17]	.07 [.01, .12]	.04 [-.01, .10]
Backward Strength	.17 [.12, .23]	.10 [.04, .15]	.08 [.03, .14]	.04 [-.02, .10]
LSA	.11 [.06, .17]	.07 [.02, .13]	.13 [.08, .19]	.09 [.03, .14]
Jiang-Conrath	-.01 [-.07, .04]	.00 [-.05, .06]	-.05 [-.11, .00]	.01 [-.04, .07]

Note. First indicates first associate, other indicates other associate cue-target relation. 200 and 1200 ms represent the SOA, which is the time from the presentation of the cue to the target. CSS: Cue set size, FSS: Feature set size, LSA: Latent Semantic Analysis distance. Sample size is 1290 cue-target pairs for first associates and 1254 pairs for other associates.

Table 8

Naming Response Latencies' Correlation and 95% CI with Semantic and

Associative Variables

Variable	FA 200	FA 1200	OA 200	OA 1200
Root Cosine	-.02 [-.08, .03]	.10 [.05, .15]	-.00 [-.06, .05]	.06 [.00, .11]
Raw Cosine	-.02 [-.07, .04]	.11 [.06, .17]	-.01 [-.06, .05]	.05 [-.01, .10]
Affix Cosine	-.01 [-.07, .04]	.06 [.01, .11]	.03 [-.03, .08]	.01 [-.05, .06]
Target Root FSS	-.03 [-.09, .02]	-.03 [-.09, .02]	-.01 [-.07, .04]	.03 [-.03, .08]
Target Raw FSS	-.04 [-.09, .02]	-.02 [-.07, .04]	-.02 [-.08, .03]	.03 [-.02, .09]
Target CSS	-.06 [-.11, -.00]	-.04 [-.09, .02]	-.02 [-.08, .03]	.01 [-.04, .07]
Cue Root FSS	-.03 [-.09, .02]	-.00 [-.06, .05]	.02 [-.03, .08]	-.02 [-.07, .04]
Cue Raw FSS	-.01 [-.07, .04]	-.01 [-.07, .04]	.02 [-.04, .07]	-.02 [-.07, .04]
Cue CSS	-.01 [-.06, .05]	-.01 [-.07, .04]	-.01 [-.07, .04]	-.01 [-.06, .05]
Forward Strength	-.02 [-.08, .03]	.02 [-.03, .08]	.04 [-.01, .10]	.04 [-.01, .10]
Backward Strength	.10 [.05, .15]	.08 [.02, .13]	.11 [.06, .17]	.04 [-.02, .09]
LSA	.06 [.01, .12]	.03 [-.02, .09]	.06 [.00, .11]	.03 [-.03, .08]
Jiang-Conrath	-.05 [-.11, .00]	.00 [-.05, .06]	-.09 [-.14, -.03]	-.01 [-.06, .05]

Note. First indicates first associate, other indicates other associate cue-target

relation. 200 and 1200 ms represent the SOA, which is the time from the

presentation of the cue to the target. CSS: Cue set size, FSS: Feature set size, LSA:

Latent Semantic Analysis distance. Sample size is 1287 cue-target pairs for first

associates and 1249 pairs for other associates.