A practical primer on processing semantic property norm data

Erin M. Buchanan[1], Simon De Deyne[2], & Maria Montefinese[3]

[1] Harrisburg University of Science and Technology

[2] University of Melbourne

[3] University of Padua

Author Note

Add complete departmental affiliations for each author here. Each new line herein must be indented, like this line.

Enter author note here.

Correspondence concerning this article should be addressed to Erin M. Buchanan, 326 Market St., Harrisburg, PA 17101. E-mail: ebuchanan@harrisburgu.edu

Abstract

Semantic property listing tasks require participants to generate short propositions (e.g., <barks>, <has fur>) for a specific concept (e.g., dog). This task is the cornerstone of the creation of semantic property norms which are essential for modelling, stimuli creation, and understanding similarity between concepts. However, despite the wide applicability of semantic property norms for a large variety of concepts across different groups of people, the methodological aspects of the property listing task have received less attention, even though the procedure and processing of the data can substantially affect the nature and quality of the measures derived from them. The goal of this paper is to provide a practical primer on how to collect and process semantic property norms. We will discuss the key methods to elicit semantic properties and compare different methods to derive meaningful representations from them. This will cover the role of instructions and test context, property pre-processing (e.g., lemmatization), property weighting, and relationship encoding using ontologies. With these choices in mind, we propose and demonstrate a processing pipeline that transparently documents these steps resulting in improved comparability across different studies. The impact of these choices will be demonstrated using intrinsic (e.g. reliability, number of properties) and extrinsic measures (e.g., categorization, semantic similarity, lexical processing). Example data and the impact of choice decisions will be provided. This practical primer will offer potential solutions to several longstanding problems and allow researchers to develop new property listing norms overcoming the constraints of previous studies.

Keywords: semantic, property norm task, tutorial

A practical primer on processing semantic property norm data

1. Available feature norms and their format

- Property listing task original work: Toglia and Battig (1978); Toglia (2009); Rosch and Mervis (1975); Ashcraft (1978)
- English: McRae, Cree, Seidenberg, and McNorgan (2005), Vinson and Vigliocco (2008), Buchanan, Holmes, Teasley, and Hutchison (2013), Devereux, Tyler, Geertzen, and Randall (2014), Buchanan, Valentine, and Maxwell (2019)
- Italian: Montefinese, Ambrosini, Fairfield, and Mammarella (2013); Reverberi, Capitani, and Laiacona (2004), Kremer and Baroni (2011)
- German: Kremer and Baroni (2011)
- Portuguese: Stein and de Azevedo Gomes (2009)
- Spanish: Vivas, Vivas, Comesaña, Coni, and Vorano (2017)
- Dutch: Ruts et al. (2004)
- Blind participants: Lenci, Baroni, Cazzolli, and Marotta (2013)

I'm sure there are more, here's what we cited recently.

Define concept, feature for clarity throughout - make sure you use these two terms consistently.

2. Pointers about how to collect the data

a. instructions, generation, verification, importance

I really like the way the CSLB did it: https://cslb.psychol.cam.ac.uk/propnorms

They showed the concept, then had a drop down menu for is/has/does, and then the participant typed in a final window. That type of system would solve about half the problems I am going to describe below about using multi-word sequences. Might be some other suggestions, but for that type of processing, you could do combinations and have more consistent data easily.

3. Typical operations performed on features

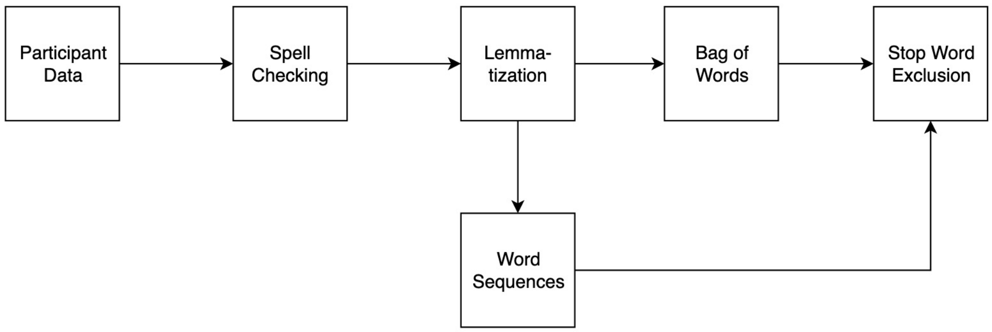


Figure 1. Flow chart of proposed semantic processing feature steps.

In the next several sections, we provide a tutorial using *R* on how data from the semantic property norm task might be processed from raw input to finalized output. Figure 1 portrays the proposed set of steps including spell checking, lemmatization, exclusion of stop words, and final processing in a multi-word sequence approach or a bag of words approach. After detailing these steps, the final data form will compared to previous norms to determine the usefulness of this approach.

Materials and Data Format

The data for this tutorial includes 17177 unique concept-feature responses for 226 concepts from Buchanan et al. (2019) that were included in McRae et al. (2005), Vinson and Vigliocco (2008), and Bruni, Tran, and Baroni (2014). The data should be structured in tidy format wherein each concept-feature observation is a row and each column is a variable (Wickham, 2014). Therefore, the data includes a `word` column with the normed concept and an `answer` column with the participant answer, as shown in Table 1.

Table 1

Tidy Data Caption

word	answer
airplane	you fly in it its big it is fast they are expensive they are at an airport you have to be trai
airplane	wings engine pilot cockpit tail
airplane	wings it flys modern technology has passengers requires a pilot can be c
airplane	wings flys pilot cockpit uses gas faster
airplane	wings engines passengers pilot(s) vary in siz
airplane	wings body flies travel

This data was collected using the instructions provided by McRae et al. (2005), however, in contrast to the suggestions for consistency detailed above (Devereux et al., 2014), each participant was simply given a large text box to include their answer. Each answer includes multiple embedded features, and the tutorial proceeds to demonstrate potential processing addressing the data in this nature. With structured data entry for participants, the suggested processing steps are reduced.

Spelling

Spell checking can be automated with the `hunspell` package in *R* (Ooms, 2018), which is the spell checking library used in popular programs such as FireFox, Chrome, RStudio, and OpenOffice. Each `answer` can be checked for misspellings across an entire column of answers, which is located in the `master` dataset. The default dictionary is American English, and the `hunspell` vignettes provide details on how to import your own dictionary for non-English languages. The choice of dictionary should also normalize between multiple varieties of the same language, for example, the `"en_GB"` would convert to British English spellings.

```r
## Install the hunspell package if necessary
#install.packages("hunspell")
library(hunspell)
## Check the participant answers
## The output is a list of spelling errors for each line
spelling_errors <- hunspell(master$answer, dict = dictionary("en_US"))
```

The result from the `hunspell()` function is a list object of spelling errors for each row of data. For example, when responding to *apple*, a participant wrote *fruit grocery store orchard red green yelloe good with peanut butter good with caramell*, and the spelling errors were denoted as *yelloe caramell*. After checking for errors, the `hunspell_suggest()` function was used to determine the most likely replacement for each error.

```r
## Check for suggestions
spelling_suggest <- lapply(spelling_errors, hunspell_suggest)
```

For *yelloe*, both *yellow yell* were suggested, and *caramel caramels caramel l camellia camel* were suggested for *caramell*. The suggestions are presented in most probable order, and using a few loops with the substitute (`gsub()`) function, we can replace all errors with the most likely replacement in a new dataset `spell_checked`. A specialized dictionary with precoded error responses and corrections could be implemented at this stage. Other paid alternatives, such as Bing Spell Check, can be a useful avenue for datasets that may contain brand names (i.e, *apple* versus *Apple*) or slang terms.

```r
## Replace with most likely suggestion
spell_checked <- master
### Loop over the dataframe
for (i in 1:nrow(spell_checked)){
  ### See if there are spelling errors
  if (length(spelling_errors[[i]]) > 0) {
    ### Loop over all errors
    for (q in 1:length(spelling_errors[[i]])){
      ### Replace with the first answer
      spell_checked$answer[i] <- gsub(spelling_errors[[i]][q],
                                      spelling_suggest[[i]][[q]][1],
                                      spell_checked$answer[i])
```

```
    }
  }
}
```

Lemmatization

The next step approaches the clustering of word forms into their lemma or head word from a dictionary. The process of lemmatizing words involves using a lexeme set (i.e., all words forms that have the same meaning, *am, are, is*) to convert into a common lemma (i.e., *be*) from a trained dictionary. In contrast, stemming involves processing words using heuristics to remove affixes or inflections, such as *ing* or *s*. The stem or root word may not reflect an actual word in the langauge, as simply removing an affix does not necessarily produce the lemma. For example, in response to *airplane*, *flying* can be easily converted to *fly* by removing the *ing* inflection. However, this same heuristic converts the feature *wings* into *w* after removing both the *s* for a plural marker and the *ing* participle marker. Several packages for *R* include customizable stemmers, notably the `hunspell`, `corpus` (Perry, 2017), and `tm` (Feinerer, Hornik, & Artifex Software, 2018) packages.

Lemmatization is the likely choice for processing property norms, and this process can be achieved by installing `TreeTagger` (Schmid, 1994) and the `koRpus` package in *R* (Michalke, 2018). TreeTagger is a trained tagger designed to annotate part of speech and lemma information in text, and parameter files are available for multiple langauges. The koRpus package includes functionality to use TreeTagger in *R*. After installing the package and TreeTagger, we will create a unique set of tokenized words to lemmatize to speed computation.

```
lemmas <- spell_checked
## Install the koRpus package
#install.packages("koRpus")
#install.packages("koRpus.lang.en")
## You must load both packages separately
```

```r
library(koRpus)
library(koRpus.lang.en)
## Install TreeTagger
#https://www.cis.uni-muenchen.de/~schmid/tools/TreeTagger/
## Find all types for faster lookup
all_answers <- tokenize(lemmas$answer, format = "obj", tag = F)
all_answers <- unique(all_answers)
```

The `treetag()` function calls the installation of TreeTagger to provide part of speech tags and lemmas for each token. Importantly, the `path` option should be the directory of the TreeTagger installation.

```r
## This function has both suppressWarnings & suppressMessages
## You should first view these to ensure proper processing
temp_tag <- suppressWarnings(
  suppressMessages(
    ## Note: the NULL option is to control for the <unknown> that appears
    ## to occur with the last word in each text
    treetag(c(all_answers, "NULL"),
            ## Control the parameters of treetagger
            treetagger="manual", format="obj",
            TT.tknz=FALSE, lang="en",
            TT.options=list(path="~/TreeTagger", preset="en"))))
```

This function returns a tagged corpus object, which can be converted into a dataframe of the token-lemma information. The goal would be to replace inflected words with their lemmas, and therefore, unknown values, number tags, and equivalent values are ignored by subseting out these from the dataset. Table 2 portrays the results from TreeTagger.

```r
## Remove all tags not using
replacement_lemmas <- temp_tag@TT.res
replacement_lemmas <- subset(replacement_lemmas,
                             #ignore punctuation
                             wclass != "punctuation" &
                             #unknown values
                             lemma != "<unknown>" &
                             #numbers
                             lemma!= "@card@" &
                             #token should change more than case
```

Table 2

Tidy Data Caption

token	tag	lemma	lttr	wclass
is	VBZ	be	2.00	verb
are	VBP	be	3.00	verb
trained	VBN	train	7.00	verb
lots	NNS	lot	4.00	noun
seats	NNS	seat	5.00	noun
wings	NNS	wing	5.00	noun

```
                                   tolower(token) != tolower(lemma))
```

From this dataset, you can use the **stringi** package (Gagolewski & Tartanus, 2019) to replace all of the original tokens with their lemmas. This package allows for replacement lookup across a large set of subsitutions. The `stri_replace_all_regex()` function includes the column of data to examine, the patterns to find (using `\\b` regular expressions to ensure word boundaries and no partial word replacements), what to replace those patterns with, and other options to ensure the original dataframe with replacement is returned. Table 3 shows the processed data at this stage.

```
## Install the stringi package
#install.packages("stringi")
library(stringi)
## Replace all the original tokens with new lemmas using \\b for word boundaries
lemmas$answer <- stri_replace_all_regex(str = lemmas$answer,
                        pattern = paste("\\b", replacement_lemmas$token, "\\b", sep = ""),
                        replacement = replacement_lemmas$lemma,
                        vectorize_all = F, list(case_insensitive = TRUE))
```

Table 3

Tidy Data Caption

word	answer
airplane	you fly in it its big it be fast they be expensive they be at an airport you have to be train
airplane	wing engine pilot cockpit tail
airplane	wing it fly modern technology have passenger require a pilot can be dan
airplane	wing fly pilot cockpit use gas fast trave
airplane	wing engine passenger pilot(s) vary in size anc
airplane	wing body fly travel

Word Sequences

Multi-word sequences are often coded to mimic a Collins and Quillian (1969) style model, with "is-a" and "has-a" type markers. If data were collected to include these markers, this step would be pre-encoded into the output data, rendering the following code unnecessary. A potential solution for processing messy data could be to search for specific part of speech sequences that mimic the "is-a" and "has-a" strings. An examination of the coding in McRae et al. (2005) and Devereux et al. (2014) indicates that the feature tags are often verb-noun or verb-adjective-noun sequences. Using TreeTagger on each concept's answer set, we can obtain the parts of speech in context for each lemma. With `dplyr` (Wickham, Francios, Henry, Muller, & Rstudio, 2019), new columns are added to tagged data to show all bigram and trigram sequences. All verb-noun and verb-adjective-noun combinations are selected, and any words not part of these multi-word sequences are treated as unigrams. Finally, the `table()` function is used to tabulate the final count of n-grams and their frequency.

```
## Create an empty dataframe
multi_words <- data.frame(Word=character(),
                          Feature=character(),
                          Frequency=numeric(),
                          stringsAsFactors=FALSE)
## Create unique word list to loop over
unique_concepts <- unique(lemmas$word)
## Install dplyr
#install.packages("dplyr")
library(dplyr)
## Loop over each word
for (i in 1:length(unique_concepts)){
  ## Create parts of speech for clustering together
  temp_tag <- suppressWarnings(
    suppressMessages(
      treetag(c(lemmas$answer[lemmas$word  == unique_concepts[i]], "NULL"),
          ## Control the parameters of treetagger
          treetagger="manual", format="obj",
          TT.tknz=FALSE, lang="en",
          TT.options=list(path="~/TreeTagger", preset="en"))))
  ## Save only the dataframe, remove NULL
  temp_tag <- temp_tag@TT.res[-nrow(temp_tag@TT.res) , ]
  ## Subset out information you don't need
  temp_tag <- subset(temp_tag,
                     wclass != "comma" & wclass != "determiner" &
                       wclass != "preposition" & wclass != "modal" &
                       wclass != "predeterminer" & wclass != "particle" &
                       wclass != "to" & wclass != "punctuation" &
                       wclass != "fullstop" & wclass != "conjunction" &
                       wclass != "pronoun")
  ## Create a temporary tibble
  temp_tag_tibble <- as_tibble(temp_tag)
  ## Create part of speech and features combined
  temp_tag_tibble <- mutate(temp_tag_tibble,
                            two_words = paste(token,
                                              lead(token), sep = "_"))
  temp_tag_tibble <- mutate(temp_tag_tibble,
                            three_words = paste(token,
                                                lead(token), lead(token, n = 2L),
                                                sep = "_"))
  temp_tag_tibble <- mutate(temp_tag_tibble,
```

```
                            two_words_pos = paste(wclass,
                                                  lead(wclass), sep = "_"))
  temp_tag_tibble <- mutate(temp_tag_tibble,
                            three_words_pos = paste(wclass,
                                                    lead(wclass), lead(wclass, n = 2L),
                                                    sep = "_"))
  ## Find verb noun or verb adjective nouns to cluster on
  verb_nouns <- grep("\\bverb_noun", temp_tag_tibble$two_words_pos)
  verb_adj_nouns <- grep("\\bverb_adjective_noun", temp_tag_tibble$three_words_pos)
  ## Use combined and left over features
  features_for_table <- c(temp_tag_tibble$two_words[verb_nouns],
                          temp_tag_tibble$three_words[verb_adj_nouns],
                          temp_tag_tibble$token[-c(verb_nouns, verb_nouns+1,
                                                   verb_adj_nouns, verb_adj_nouns+1,
                                                   verb_adj_nouns+2)])
  ## Create a table of frequencies
  word_table <- as.data.frame(table(features_for_table))
  ## Clean up the table
  word_table$Word <- unique_concepts[i]
  colnames(word_table) = c("Feature", "Frequency", "Word")
  multi_words <- rbind(multi_words, word_table[ , c(3, 1, 2)])
}
```

This procedure produces mostly positive output, such as *fingers-have_fingernails* and *couches-have_cushions*. One obvious limitation is the potential necessity to match this coding system to previous codes, which were predominately hand processed. Further, many similar phrases, such as the ones for *zebra* shown below may require fuzzy logic matching to ensure that the different codings for *is-a-horse* are all combined together, as shown in Table 4.

Bag of Words

The bag of words approach simply treats each token as a separate feature to be tabulated for analysis. After stemming and lemmatization, the data can be processed as single word tokens into a table of frequencies for each cue word. The resulting dataframe is

Table 4

Tidy Data Caption

Word	Feature	Frequency
zebra	be_horse	1
zebra	be_similar_horse	1
zebra	build_horse	1
zebra	horse	22
zebra	horse-like	1
zebra	look_similar_horse	1
zebra	related_horse	1
zebra	resemble_small_horse	1
zebra	run_fast_horse	1
zebra	run_horse	1
zebra	sound_horse	1
zebra	stripe_similar_horse	1

each cue-feature combination with a total for each feature.

```
## Create an empty dataframe
bag_words <- data.frame(Word=character(),
                        Feature=character(),
                        Frequency=numeric(),
                        stringsAsFactors=FALSE)
## Loop over each word
for (i in 1:length(unique_concepts)){
  ## Create a table of frequencies
  word_table <- as.data.frame(table(
    ## Tokenize the words
    tokenize(
      ## Put all answers together in one character string
      paste0(lemmas$answer[lemmas$word == unique_concepts[i]], collapse = " "),
      format = "obj", tag = F)))
```

```
  ## Clean up the table
  word_table$Word <- unique_concepts[i]
  colnames(word_table) = c("Feature", "Frequency", "Word")

  bag_words <- rbind(bag_words, word_table[ , c(3, 1, 2)])
}
## Remove punctuation
bag_words <- bag_words[-c(grep('^[[:punct:]]',bag_words$Feature)), ]
```

The top ten features in zebra indicate a match to the multi-word sequence approach but the inclusion of words such as *be, in, a* indicate the need to remove irrelevant words listed with features.

kable(zebra[1:10,], “latex”, booktabs = T, row.names = F) %>% kable_styling(position = “center”)

Stopwords

As shown in Figure 1, the next stage of processing would be to exclude stopwords, such as *the, of, but*, for either the multi-word sequence or bag of word style processing. The `stopwords` package (**???**) includes a list of stopwords for more than 50 languages. For multi-word sequence processing, these values can be removed by subseting the data to exclude stopwords as unigrams.

```
## Install the stopwords package or use tm
#install.packages("stopwords")
library(stopwords)
## Remove stop words from either processing approach
multi_words <- subset(multi_words,
                      !(Feature %in% stopwords(language = "en",
                                               source = "snowball")))

bag_words <- subset(bag_words,
                    !(Feature %in% stopwords(language = "en",
                                             source = "snowball")))
```

Descriptive Statistics

```
## [1] 0.9836455
```

```
## [1] 0.7351418
```

```
## [1] 0.6603825
```

```
## [1] 0.9163408
```

```
## [1] 0.7155022
```

```
## [1] 0.8167169
```

make a table here of the stuff talk about deleting low features or not d. identify cut off for idiosyncratic features (should it be necessary?)

Internal Comparison of Approach

Compare this data processing to hand processed data from B2019

```
##        raw_b        raw_m        raw_v translated_b translated_m
##    0.6899807    0.3764903    0.5926762    0.7243672    0.5753183
## translated_v
##    0.5817829
```

External Comparison of Approach

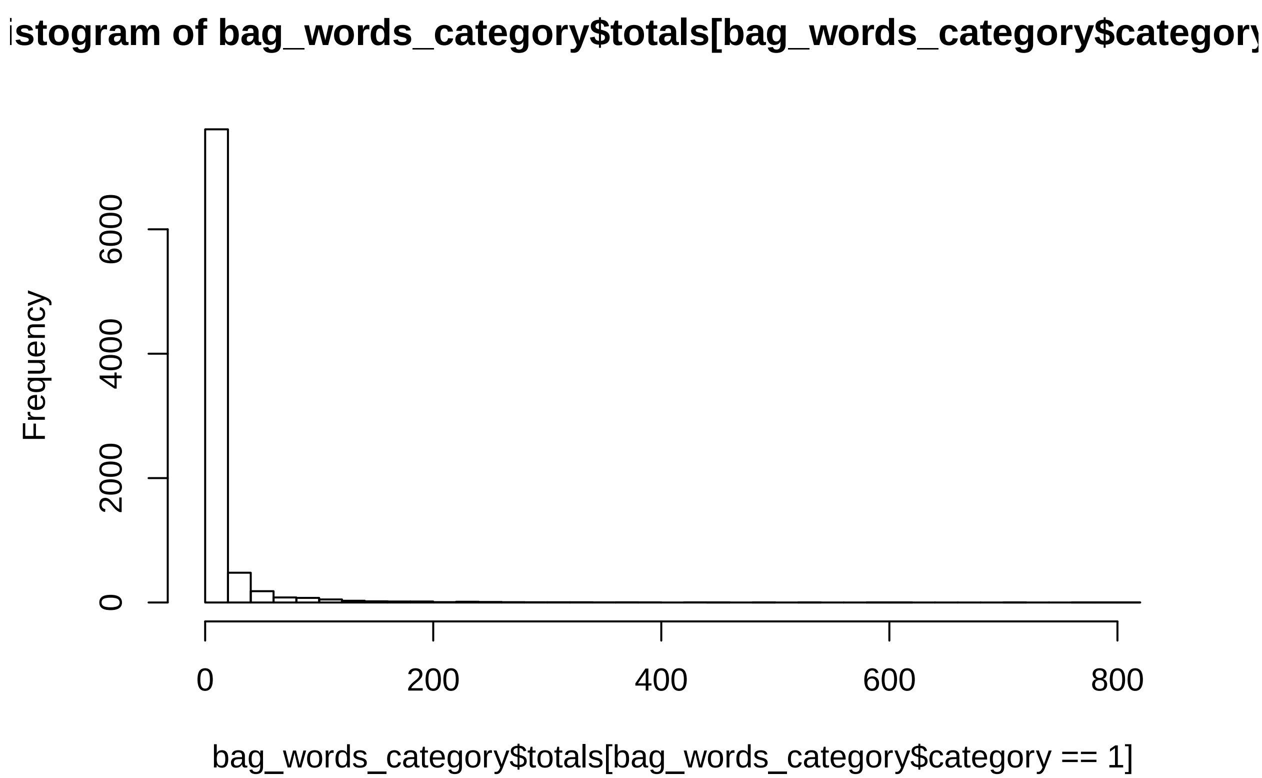
Compare to the MEN dataset

```
## [1] 0.6889117
```

Ontology and Categorization

```
##  [1] 0.9477885 0.8802228 0.8768643 0.8775418 0.8776403 0.8761919 0.8762623
##  [8] 0.8723146 0.8723403 0.8657468 0.8660341 0.8660926 0.8661895 0.8662974
## [15] 0.8662678 0.8657396 0.8658517 0.8641960 0.8634386 0.8573610 0.8250660
## [22] 0.8249962 0.8252634 0.8255298 0.7192209 0.7193813 0.7193717 0.7197155
## [29] 0.7193555 0.7189437 0.7190156 0.7191427 0.7185243
```

```
##
##    1    2    3    4    5    6
## 8613   17    3   13   11    5
```




```
##         1         2         3         4         5         6
##   11.6864  193.2353 1843.0000  150.6923  124.4545  442.0000
```

```
##         1         2         3         4         5         6
```

```
##  36.57800 161.36238 520.74274  97.93313  95.65497 116.06679

##     1     2     3     4     5     6
##     1    43  1260    70    44   247

##     1     2     3     4     5     6
##   810   542  2262   383   362   550
```

Discussion

References

Ashcraft, M. H. (1978). Property norms for typical and atypical items from 17 categories: A description and discussion. *Memory & Cognition*, *6*(3), 227–232. doi:10.3758/BF03197450

Bruni, E., Tran, N. K., & Baroni, M. (2014). Multimodal Distributional Semantics. *Journal of Artificial Intelligence Research*, *49*, 1–47. doi:10.1613/jair.4135

Buchanan, E. M., Holmes, J. L., Teasley, M. L., & Hutchison, K. A. (2013). English semantic word-pair norms and a searchable Web portal for experimental stimulus creation. *Behavior Research Methods*, *45*(3), 746–757. doi:10.3758/s13428-012-0284-z

Buchanan, E. M., Valentine, K. D., & Maxwell, N. P. (2019). English semantic feature production norms: An extended database of 4436 concepts. *Behavior Research Methods*. doi:10.3758/s13428-019-01243-z

Collins, A. M., & Quillian, M. R. (1969). Retrieval time from semantic memory. *Journal of Verbal Learning and Verbal Behavior*, *8*(2), 240–247. doi:10.1016/S0022-5371(69)80069-1

Devereux, B. J., Tyler, L. K., Geertzen, J., & Randall, B. (2014). The Centre for Speech, Language and the Brain (CSLB) concept property norms. *Behavior Research Methods*, *46*(4), 1119–1127. doi:10.3758/s13428-013-0420-4

Feinerer, I., Hornik, K., & Artifex Software, I. (2018). tm: Text Mining Package. Retrieved from https://cran.r-project.org/web/packages/tm/index.html

Gagolewski, M., & Tartanus, B. (2019). stringi: Character String Processing Facilities. Retrieved from https://cran.r-project.org/web/packages/stringi/index.html

Kremer, G., & Baroni, M. (2011). A set of semantic norms for German and Italian. *Behavior Research Methods*, *43*(1), 97–109. doi:10.3758/s13428-010-0028-x

Lenci, A., Baroni, M., Cazzolli, G., & Marotta, G. (2013). BLIND: A set of semantic feature norms from the congenitally blind. *Behavior Research Methods*, *45*(4), 1218–1233. doi:10.3758/s13428-013-0323-4

McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods*, *37*(4), 547–559. doi:10.3758/BF03192726

Michalke, M. (2018). koRpus: An R Package for Text Analysis. Retrieved from https://cran.r-project.org/web/packages/koRpus/index.html

Montefinese, M., Ambrosini, E., Fairfield, B., & Mammarella, N. (2013). Semantic memory: A feature-based analysis and new norms for Italian. *Behavior Research Methods*, *45*(2), 440–461. doi:10.3758/s13428-012-0263-4

Ooms, J. (2018). The hunspell package: High-Performance Stemmer, Tokenizer, and Spell Checker for R. Retrieved from https://cran.r-project.org/web/packages/hunspell/vignettes/intro.html{\#}setting{_}a{_}language

Perry, P. O. (2017). corpus: Text Corpus Analysis. Retrieved from http://corpustext.com/

Reverberi, C., Capitani, E., & Laiacona, E. (2004). Variabili semantico lessicali relative a tutti gli elementi di una categoria semantica: Indagine su soggetti normali italiani per la categoria “frutta". *Giornale Italiano Di Psicologia*, *31*, 497–522.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology*, *7*(4), 573–605. doi:10.1016/0010-0285(75)90024-9

Ruts, W., De Deyne, S., Ameel, E., Vanpaemel, W., Verbeemen, T., & Storms, G. (2004).

Dutch norm data for 13 semantic categories and 338 exemplars. *Behavior Research Methods, Instruments, & Computers*, *36*(3), 506–515. doi:10.3758/BF03195597

Schmid, H. (1994). Probabilistic Part-of-Speech Tagging Using Decision Trees. doi:10.1.1.28.1139

Stein, L., & de Azevedo Gomes, C. (2009). Normas Brasileiras para listas de palavras associadas: Associação semântica, concretude, frequência e emocionalidade. *Psicologia: Teoria E Pesquisa*, *25*, 537–546. doi:10.1590/S0102-37722009000400009

Toglia, M. P. (2009). Withstanding the test of time: The 1978 semantic word norms. *Behavior Research Methods*, *41*(2), 531–533. doi:10.3758/BRM.41.2.531

Toglia, M. P., & Battig, W. F. (1978). *Handbook of semantic word norms*. Hillside, NJ: Earlbaum.

Vinson, D. P., & Vigliocco, G. (2008). Semantic feature production norms for a large set of objects and events. *Behavior Research Methods*, *40*(1), 183–190. doi:10.3758/BRM.40.1.183

Vivas, J., Vivas, L., Comesaña, A., Coni, A. G., & Vorano, A. (2017). Spanish semantic feature production norms for 400 concrete concepts. *Behavior Research Methods*, *49*(3), 1095–1106. doi:10.3758/s13428-016-0777-2

Wickham, H. (2014). Tidy Data. *Journal of Statistical Software*, *59*(10), 1–23. doi:10.18637/jss.v059.i10

Wickham, H., Francios, R., Henry, L., Muller, K., & Rstudio. (2019). dplyr: A Grammar of Data Manipulation. Retrieved from https://cloud.r-project.org/web/packages/dplyr/index.html