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The University of South Florida free association, rhyme, and word fragment norms

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Preexisting word knowledge is accessed in many cognitive tasks, and this article offers a means for indexing this knowledge so that it can be manipulated or controlled. We offer free association data for 72,000 word pairs, along with over a million entries of related data, such as forward and backward strength, number of competing associates, and printed frequency. A separate file contains the 5,019 normed words, their statistics, and thousands of independently normed rhyme, stem, and fragment cues. Other files provide $n \times n$ associative networks for more than 4,000 words and a list of idiosyncratic responses for each normed word. The database will be useful for investigators interested in cuing, priming, recognition, network theory, linguistics, and implicit testing applications. They also will be useful for evaluating the predictive value of free association probabilities as compared with other measures, such as similarity ratings and co-occurrence norms. Of several procedures for measuring preexisting strength between two words, the best remains to be determined. The norms may be downloaded from www.psychonomic.org/archive/.

The purpose of this article is to make the largest free association database collected in the United States available to interested researchers and scholars. More than 6,000 participants produced nearly three quarters of a million responses to 5,019 stimulus words.

What Do Free Association Norms Measure?

With high degrees of average reliability ($r = .89$), free association response probabilities index the likelihood that one word can cue another word to come to mind with minimal contextual constraints in effect (Nelson, McEvoy, & Dennis, 2000). Free association probabilities provide a relative, rather than an absolute, index of what is generally called *forward strength*, because they are sensitive to other associates activated by the cue word that compete for production (Gillund & Shiffrin, 1984; Nelson, Dyrdal, & Goodmon, in press). In short, given a cue, free association probabilities index the relative accessibility of related words in memory.

We assume that free association taps into lexical knowledge acquired through world experience. Such experience creates associative structures involving the representations of words and the links that bind them together. These structures conform to the general constraints underlying *small-world* networks (Steyvers & Tenenbaum, in press). Like the semantic networks of WordNet, associative networks are sparse, they exhibit strong local clustering, and they have short average path lengths between words. An average of only three associative steps is required to get from any one word in our norms to any other.

Associative structures capture the shared lexical experiences of many people. They are dynamic because they are derived from the stream of everyday experience that changes gradually over time but that can produce precipitous temporary effects; for example, because of the movie, the primary free association response in our norms to *instinct* is *basic*. Norms must be used in conjunction with knowledge about current trends and local culture. They are also dynamic because they are sensitive to experience that deviates from the norm. For example, for words related to drug and alcohol use, the associative structures of substance abusers are different from the norm (Reich & Goldman, in press; Stacy, 1997).

Although the language of association theory is used to describe the procedures and findings of experiments that rely on free association probabilities, this task appears to capture both associative knowledge and aspects of meaning. They index the knowledge that lemons are sour, that birds fly, and so on. Many researchers have attempted to draw a distinction between the effects of association and meaning by creating materials that are semantically but, ostensibly, not associatively related (e.g., for reviews, see Hutchison, 2003; Lucas, 2000). However, given the small-

world nature of associative links, such attempts will be difficult if not futile. If only a few associative links separate most words, how can it be said that two words are not associated? The problem is not in showing that pairs of words are meaningfully related in some semantic classification, but in showing that meaningfully related pairs are not associated. Useful work on semantic classification can proceed apace without belaboring the fatuous issue of association versus meaning. Not only can we not say that two words are unassociated, but also none of the procedures for measuring preexisting strength assess the conditions of acquisition. Norms provide no knowledge of when, where, and how any measured preexisting link was learned.

How Can Free Association Norms Be Used in Research?

Free association norms are useful for several reasons. First, geneticists map genes, geologists map the earth, and psychologists are justified in mapping the links among concepts. Free association norms offer a means for constructing maps of the lexical knowledge that is most accessible to people sharing a language and a cultural heritage. Understanding the organization of word knowledge continues to be a significant problem. Second, free association probabilities can be treated as results that inform us about the nature of free association as a knowledge retrieval task (Nelson et al., 2000). Linguistic analyses of the responses can tell us about the likelihood of searching within particular domains of information as a function of information contained in the cue word.

Third, free association probabilities are useful because they predict memory performance and other behaviors (Nelson et al., 2000; Nelson, McKinney, Gee, & Janczura, 1998). Preexisting associative structures play a significant role in both recall and recognition; for example, cued recall is more likely for stronger than for to weaker cues. Both recall and recognition are more likely when the associates of studied words are more connected to each other. Performance in standard memory tasks is influenced by the structure of preexisting knowledge about the words used in the experiments. Nearly 50% of the variance in extralist cued recall can be explained by knowledge that learners posses prior to the experiment (Nelson & Zhang, 2000). Understanding many key issues in memory, priming, language, reasoning, development, and other areas will depend on knowing what people know and how they use this knowledge to achieve the goals of various tasks. Mental processes such as comprehension, elaboration, retrieval, and so on cannot effectively be understood in isolation from the materials on which these processes are based (Jenkins, 1979). The main justification for using normative data is that researchers benefit from knowledge of what their participants are likely to know in selecting materials for their research.

Free association norms have other uses as well. They can be compared with other norms in order evaluate the validity of different types of procedures for indexing proximity (e.g., Steyvers & Tenenbaum, in press) and for evaluating statistical models of semantic representation (Dennis, 2003; Griffiths & Steyvers, 2002). In empirical studies involving materials variables (e.g., printed frequency), associative norms can be used to avoid confounding the manipulated variable with other features. Norms also provide baseline data that can be used to determine whether some specialized population deviates from the norm (Reich & Goldman, in press; Stacy, 1997). Free association procedures can also be used to provide an implicit assessment of the effects of training, therapy, and marketing.

METHOD

Participants

An average of 149 ($SD = 15$) participants were presented with 100–120 English words in a booklet containing 25–30 words per page, with the order of the pages unsystematically randomized across booklets. All received course credit for their participation.

Procedure

The participants were asked to write the first word that came to mind that was meaningfully related or strongly associated to the presented cue word. For example, given *book* _____ , they might write *read*. This is a discrete free association task, because each participant is asked to produce only a single associate to each word.

Materials

The great majority of the normed words are nouns (76%), but adjectives (13%), verbs (7%), and other parts of speech are represented. In addition, 16%, or 803 words, are identified as homographs. The selection of specific words for norming was always driven by research needs. At first, many were selected because of their potential utility as test cues for prompting the recall of related words. Others were selected because they were produced as responses in our rhyme norms, and we wanted to be able to cue the recall of the same word with either a rhyme cue or a meaning cue (e.g., Nelson & McEvoy, 1979). Some words were added because of work on priming (Bajo, 1988; Canas, 1990; McEvoy, 1988; Nelson & Goodmon, 2002), and others were added because of interest in the concreteness issue (Nelson & Schreiber, 1992). Many more were added in later years because they completed entire associative sets. By knowing a word's associates, as well as the associates of these associates, we could set up an $n \times n$ associative matrix in which a normed word and all of its associates were listed as column names and again as row names. This procedure allowed us to count a word's associate-to-associate links (its connectivity), as well as its associate-to-target links, or resonance (e.g., Nelson, McEvoy, & Pointer, 2003). Associative matrices were completed or nearly completed for 4,097 words (Appendix C in the archive).

Data Analysis

Each word and the frequencies of its responses were recorded, and D.L.N., C.L.M., or both reviewed the classifications of all responses throughout the project. Spelling errors were corrected, and rules were developed to pool items that, in our judgment, should be put together. For example, *woman* produced *man* as the dominant response, but a few participants wrote *men*. Instead of treating each of these responses as separate items, the count for *men* was pooled with the count for *man*. Insofar as plurals were concerned, the rule was to pool minority responses with the majority when the same word stem was involved. Similar rules were used for tense and grammatical form. In general, pooling was used reluctantly and only when it seemed justified. We engaged this practice because our interest was in assessing

the relative strength of a given response for use in cuing and priming studies and we assumed, rightly or wrongly, that a more accurate indication would be provided by pooled than by separate tabulations. Because of this practice, scholars interested in specific forms of response, such as plurality, should be careful in using these norms.

RESULTS
The Database

A brief description of what can be found in each of the four Excel format appendices is provided below. This information is presented in more detail on the Web site in the Read Me files that accompany each appendix. The references for all three appendices are available in a common file in the archive.

Appendix A

Appendix A is useful to anyone needing free association norms. All 72,186 cue–target response pairs are listed alphabetically by cue, and within cue, by target. In addition, 33 columns provide more than a million pieces of information related to associative links between the word pairs, as well as information related to individual cue and target properties. This information is represented on two Excel sheets, with A–System cues on Sheet 1 and Tab–Zucchini cues on Sheet 2. A complete example of this table is too large for the journal, but an illustration showing the first 8 columns for the cue word A is shown in Table 1. Finally, this file can be realphabetized by target, and this ordering will display all of the normed cues that produce that target as an associate, along with the linked information. This format will be useful for anyone who has already selected a target word and is looking for a potential cue or prime word.

Appendix B

Appendix B presents the 5,019 normed words, listed alphabetically, and associative as well as frequency and other data that will be useful as targets for experiments on single-item recognition and for experiments on non-semantic cuing. This appendix presents independent set size and strength norms for beginning stem cues, ending stem cues, beginning fragment cues, and ending fragment cues. Each of the targets presented in this file can be looked up in Appendix A whenever an investigator needs both a nonsemantic and a semantic cue for the same target word—for example, *good* and *be_ _* as cues for *best*. All of the target words appearing in this file are cross-referenced in the meaning files, making it possible to manipulate type of cue or type of prime while holding normative cue-to-target strength, as well as other word characteristics, constant. Table 2 provides a list of what can be found in Appendix B.

Appendix C

Appendix C contains an alphabetical listing of the $n \times n$ associative matrices showing associate-to-target links (resonance) and associate-to-associate links (connectivity) for thousands of normed words. The matrices provide a concrete representation of associative structure for a given word. As is shown in Table 3, the word *dinner* has a set of five associates, including *supper*, *eat*, *lunch*, *food*, and *meal*. These norms were created by norming *dinner* and then, with independent samples of participants, norming each of its associates. *Dinner* is shown in the top left corner of the matrix, and its associates are printed in full in the first column. The first three letters of each associate is also printed at the top of the remaining columns.

The first row provides the target and the free association probabilities for each of its associates (the self-strength of *dinner* is assigned a 1.0 for theoretical reasons). The remaining rows should also be read from left to right. In the first column, they show the free association probabilities for each associate-to-target link (e.g., *supper* produces *dinner* with a probability of .55). In the remaining columns, they show the probabilities of associate-to-associate links (e.g., *supper* produces *eat* with a probability of .02). The

Table 1
An Illustration of Part of the Information in Appendix A for the First Word
in the Norms

Cues	Targets	Target Normed?	Sample Size	No. Subjects Producing Target	Forward Strength	Backward Strength	Mediated Strength
A	ALPHABET	YES	152	10	0.066	0.046	0.002
A	AN	NO	152	4	0.026	missing	0
A	AND	NO	152	2	0.013	missing	0
A	APPLE	YES	152	2	0.013	0	0
A	B	NO	152	69	0.454	missing	0
A	GRADE	YES	152	9	0.059	0.277	0
A	GREAT	YES	152	2	0.013	0	0
A	LETTER	YES	152	6	0.039	0	0.003
A	ONE	YES	152	2	0.013	0	0
A	PLUS	YES	152	5	0.033	0	0
A	THE	NO	152	10	0.066	missing	0
A	WORD	YES	152	2	0.013	0	0
A	Z	NO	152	3	0.020	missing	0

Table 2
Information in Appendix B

Column Label	Definition
Targets	Words normed in free association
Sample Size	Number of participants
Set Size	Number of different target associates, or network size
Set Size + Idiosyncratic	Target set size + idiosyncratic responses
Frequency (K&F)	Printed frequency in Kučera and Francis (1967) norms
Concreteness (Scale 1–7)	Concreteness ratings for the target word
Homograph? (Letter = Yes)	Is the target a homograph? Letter indicates norms used.
Part of Speech	Part of speech of the target determined by dictionary
Mean Connectivity	Mean number of associate-to-associate links for target
Connectivity Strength	Summed strength of target's associate-to-associate links
Resonance Probability	Probability that target's associates produce it as an associate
Resonance Strength	Summed strength of target's associate-to-target links
Accessibility Index	Number of cues that produce the target as a response
Non-Responses	No response, illegible responses, swear words
Ending Stem Set Size	Number of different words produced in free association after hearing end of target as a rhyme cue
Ending Stem Strength	Probability of producing target in free association after hearing end of target as a rhyme cue
Beginning Stem Set Size	Number of different words produced in free association after hearing beginning letters of target as a cue
Beginning Stem Strength	Probability of producing target in free association after hearing beginning letters of target as a cue
Ending Fragment Cues	Words with missing letters replaced by spaces presented as free association cues
Ending Fragment Set Size	Number of different words produced in free association for a visually presented ending fragment cue
Ending Fragment Strength	Probability of producing target in free association for visually presented ending fragment cue
Beginning Fragment Cues	Words with missing letters replaced by spaces presented as free association cues
Beginning Fragment Set Size	Number of different words produced in free association for a visually presented beginning fragment cue
Beginning Fragment Strength	Probability of producing target in free association for visually presented beginning fragment cue

associates of *dinner* are highly connected, but the associates for most words are sparsely connected. In PIER2 (Nelson & Zhang, 2000), the sum of the strengths in the first column provides an estimate of resonance strength (for *dinner*, the resonance strength is 2.03). The sum of the strengths in the remaining columns provides an estimate of connectivity strength (for *dinner*, the connectivity strength is $.62 + .68 + .20 + 1.36 + .20 = 3.06$). The sum of resonance and connectivity strength estimates the activation strength of the target when studied ($2.03 + 3.07 = 5.09$). Finally, the absence of a value in the matrix is interpreted as an indication either that there is no connection or that it is too weak to be measured by direct, single-response free association.

Table 3
$n \times n$ Associative Matrix for *Dinner*

Cue	DIN	SUP	EAT	LUN	FOO	MEA
DINNER	1.00	0.54	0.11	0.10	0.09	0.09
SUPPER	0.55	–	0.02	0.03	0.17	0.01
EAT			–		0.40	0.02
LUNCH	0.27	0.02	0.08	–	0.21	0.06
FOOD			0.41	0.01	–	0.02
MEAL	0.21	0.06	0.06	0.06	0.49	–
Summed strength	2.03	.62	.68	.20	1.36	.20

Appendix D

Appendix D presents all of the normed words and their idiosyncratic responses. Idiosyncratic responses are not presented in Appendix A, because they are produced by a single individual and are unreliable (Nelson & Schreiber, 1992). The participants produced 111,157 idiosyncratic responses, which comes to an average of 22.15 such responses for each normed word. On average, more idiosyncratic responses are produced than responses given by 2 or more participants. This production was highly variable across different words, ranging from 1 to 73 responses, with a standard deviation of 10 words. Only 111,026 idiosyncratic responses are reported in this appendix, because some were missing due to of errors of various types. Rather than spending weeks tracking down the errors, we are simply reporting what we have. As an illustration of what can be found in this appendix, Table 4 provides the idiosyncratic responses for the word *dinner*. As can be seen, these associates tend to be related to the cue, but because they are unreliable, we never included them in the estimate of set size for research purposes. A column presenting the sum of set size plus idiosyncratic responses is available in Appendix B for those who may be interested in comparing values.

Table 4
The Normed Words, Their Idiosyncratic Responses,
and the Probabilities of These Responses

Normed Word	Response	Probability
DINNER	BELL	.009
DINNER	DANCE	.009
DINNER	GUEST	.009
DINNER	HUNGRY	.009
DINNER	JACKET	.009
DINNER	PARTY	.009
DINNER	REPAST	.009
DINNER	STEAK	.009
DINNER	TABLE	.009

DISCUSSION

Why should free association norms, as opposed to other procedures, be used to estimate the preexisting strength between two words? One reason is that free association has a long history as a reliable task for measuring connection strengths (Cramer, 1968; Deese, 1965; Jenkins & Palermo, 1964; Nelson et al., 2000). Another reason is that free association offers two advantages over rating pairs of words for associative similarity. Norming a single word provides a list of its associates, whereas a similarity rating provides a measure for a single pair. Mapping a word's associative structure in an $n \times n$ format is less complicated with free association, because a word's associates do not have to be discovered by collecting ratings for thousands of words. The second advantage is that free association probabilities predict recall success more accurately than do ratings in both extralist and intralist cuing procedures (Nelson et al., in press). When it comes to predicting recall, free association probabilities perform better than ratings. However, recent work on co-occurrence statistics offers a promising alternative for predicting memory performance (Landauer & Dumais, 1997). The assumption is that the co-occurrence of words in text can be used to index semantic similarity. A text that mentions *lions* is likely to mention animals that lions prey upon. Latent semantic analysis (LSA) uses co-occurrences and a technique known as single-value decomposition for locating words in semantic space. Tens of thousands of words and texts are involved in the computations, and words appearing in similar texts are placed in similar regions of a multidimensional space of 200–400 dimensions.

LSA's similarity index may be related to free association probabilities and may predict recall success. It is modestly correlated with forward strength in our norms ($r = .27$, $n = 49,362$; Maki, McKinley, & Thompson, 2004). Unfortunately, LSA similarity is more weakly correlated with extralist cued recall probability ($r = .07$, $n = 2,201$) than with free association probabilities ($r = .30$, $n = 2,201$; see also Steyvers, Shiffrin, & Nelson, in press). However, although LSA statistics do not predict recall, they effectively predict reading (Landauer & Dumais, 1997; Landauer, Foltz, & Laham, 1998). Free association is a better predictor for recall because both free association and cued recall require the recovery of a related word from memory, given a cue. In contrast, LSA similarity is

more likely to be a better predictor of reading comprehension than is free association, because textual material provides the basis for measuring semantic similarity. Different kinds of maps for measuring lexical knowledge are likely to be needed for predicting different kinds of cognitive performance.

Free association is more useful for predicting recall than are similarity ratings or LSA, but it has shortcomings. First, the discrete free association procedure avoids problems of response chaining and retrieval inhibition (McEvoy & Nelson, 1982), but the single-response requirement reduces the chances of observing weak associates (Nelson et al., 2000). Free association probabilities underestimate the strengths of directly linked but weak associates, and this point should be kept in mind when using norms to build materials for research.

The second limitation is that free association provides a relative, not an absolute, index of strength. Knowing that the response *read* is produced by 43% of the participants to the cue *book* does not tell us how strong this response is in any absolute sense; it indicates that this response is stronger than *study*, which was produced by 5.5% of the participants. Free association norms, like similarity ratings, provide reasonable approximations to interval scale measures, but as far as we know, no measure of absolute preexisting strength exists. Furthermore, free association provides an index of strength that comes without an independent measure of variance. It is a proportion, so it has a binomial variance that is predictable from this proportion, but this shortcoming may limit the usefulness of this index in some situations.

Researchers also need to be concerned about the generalizability of free association norms across cultures and regions. Kiss, Armstrong, and Milroy (1972) normed more than 8,000 words in Great Britain. When we compared the associates of words common to the two sets of norms, we decided that the differences were too great for the kind of work we anticipated doing, so we continued collecting our own. Free association is also sensitive to regional differences. For example, associates to *apple* may be different in Florida than in other locations where apple trees and traditions of apple pie and picking apples are more frequent. Although Floridians know about apples, many have never seen or climbed a real apple tree, and their most frequent response is *red*, with *tree* and *pie* given infrequently. Although the present norms have been used successfully in many places, the important point is that free association norms, or norms of any kind, must be used with sensitivity to local word usage, as well as to events that may temporarily alter strength. Finally, free association norms are sensitive to personal individual differences in experience. Responses to drug- and alcohol-related words are stronger for drug users (Stacy, 1997) and heavy drinkers (Reich & Goldman, in press). Cultural, regional, temporal, and individual influences must be kept in mind when using free association norms in constructing materials for experiments.

These considerations indicate that free association is an imperfect but useful tool. Difficult as they are to collect,

such norms offer better maps for predicting performance in certain cognitive tasks, and if anything, more norms are needed. A case can be made for a national norming study involving thousands of words. The measurement issue begs for additional research, because the importance of mapping lexical knowledge justifies such attention if the field is going to answer the fundamental question of how word knowledge interacts with ongoing cognitive performance.

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