The *lrd* Package: An *R* Package and Shiny Application for Processing Lexical Data

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Abstract

Recall testing is a common assessment to gauge memory retrieval. Responses from these tests can be analyzed in several ways; however, the output generated in a recall study typically requires manual coding that can be time intensive and error-prone before analyses can be conducted. To address this issue, this article introduces *lrd* (Lexical Response Data), a set of open-source tools for quickly and accurately processing lexical response data that can be used either from the *R* command line or through an *R Shiny* graphical user interface. First, we provide an overview of this package and include a step-by-step user guide for processing both cued- and free-recall responses. For validation of *lrd,* we used *lrd* to recode output from cued, free, and sentence-recall studies with large samples and examined whether the results replicated using *lrd* scored data. We then assessed the inter-rater reliability and sensitivity and specificity of the scoring algorithm relative to human-coded data. Overall, *lrd* is highly reliable and shows excellent sensitivity and specificity, indicating that recall data processed using this package are remarkably consistent with data processed by a human coder.

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The *lrd* Package: An R Package and Shiny Application for Processing Lexical Data

People are generally able to acquire new knowledge with relative ease. Much of our understanding of how individuals organize and store learned information comes from the use of recall tests (see Polyn et al., 2009 for a review). Typical recall paradigms present participants with a set of items to learn within a controlled environment, and participants are asked to recall them on a later test. Recall can either be assessed via free report, in which individuals report information from memory with few, if any, cues or constraints (free-recall), or by the presentation of a cue that is used to direct their retrieval (cued-recall). Recall tests are routine in memory research, including studies investigating the effectiveness of different memory strategies (e.g., deep vs. shallow encoding tasks; Craik & Lockhart, 1972), survival processing (e.g., assessing memory for contaminated objects; Gretz & Huff, 2019), and metacognition (e.g., accuracy between judgments of learning and recall; Koriat & Bjork, 2005). Furthermore, because studies often employ words as stimuli (i.e., cue-target pairs), a large body of research has been conducted to explore how the lexical properties of the cue and target can influence later recall (word frequency, Criss et al., 2011; e.g., concreteness, Paivio et al., 1988) or how the semantic relationships between pairs affect recall (Maxwell & Buchanan, 2020). Though the research questions differ, recall studies generally employ lexical information in some capacity, either as the stimuli that participants are required to study, the dependent variable of interest, or more commonly, through a combination of the two.

Cued-recall testing is a well-known paradigm and has been used extensively in psychological research. For example, cursory searches of Google Scholar for the keywords “cued-recall” and “free-recall” conducted in April of 2021 yielded approximately 18,000 and 48,000 publications, respectively, published since the year 2000. These results spanned multiple subfields of Psychology including neuroscience, psycholinguistics, and cognitive aging. Additionally, the rise of the internet combined with more powerful computers, has made it easier for researchers conduct recall testing by providing access to platforms for participant recruitment and computer-based testing. Furthermore, in addition to aiding data collection, the internet has allowed information about lexical characteristics of stimuli (such as word length or frequency) to be more efficiently collected and organized. As a result, the past two decades have provided researchers with access to a growing number of normed databases with which to construct lexical stimuli for use within recall studies (e.g., The English Lexicon Project, Balota et al., 2007; The Small World of Words, De Deyne et al., 2019; The Semantic Priming Project, Hutchison et al., 2013). Recently, online tools to aid researchers in selecting stimuli from the appropriate normed database have been made available (e.g., The Linguistic Annotated Bibliography, Buchanan et al., 2019b) and computer applications such as the *lexOPS* package for *R* ­(Taylor et al., 2020) have been developed to automate the stimuli selection process entirely while controlling for several types of word properties. Though there has been a proliferation of datasets and tools used to aid researchers with stimuli creation, little attention has been given to developing tools that assist researchers with processing the large amounts of data that are generated from these studies.

Since studies investigating memory using both cued- and free-recall testing typically generate large amounts of lexical text data, processing the output is often time-consuming and tedious. Furthermore, the number of participants recruited to take part in these studies has drastically increased within the past decade, partially as a response to the replication crisis (Maxwell et al., 2015), which has resulted in an even greater need for efficient and accurate methods for processing recall data. As such, the purpose of this paper is to introduce the *lrd* (lexical response data) package, which has been designed to provide researchers with a set of simple and freely accessible tools that can be used to speed up scoring of text responses from recall studies.

Output from cued- and free-recall tests are generally scored by matching participants’ responses to the various stimuli against a scoring key containing the correct set of responses. Though typed responses are unquestionably easier to process relative to handwritten responses, each response item must still be manually checked against the key to determine accuracy. For large datasets, manually scoring data is arduous, resulting in hours of checking participant responses against an answer key. While such tasks can generally be divided across research assistants, manual scoring may still prove to be a time-consuming endeavor depending on the amount of data requiring processing. Furthermore, multiple scorers can potentially introduce error in the coded responses, as inconsistencies across raters may arise if not properly controlled for (i.e., addressing participant misspellings, plural vs. singular nouns, alternate tenses, etc.) and scoring discrepancies are not resolved. Finally, if scoring is not conducted blind to experimental conditions, potential biases may influence the final scored output.

To reduce the overall time spent processing raw output and potential coder inaccuracies, an alternative method is to automate the data coding processes by employing a computer application that can automatically compare participant responses relative to a scoring key. However, simple text matching of responses does not account for participant errors in responses, such as misspellings or embedded coding provided by the survey software (e.g., extra spaces, tabs, newlines, etc.). These items still represent a correct memory; however, more sophisticated text processing is required. While a human scorer can easily correct any minor character additions, omissions, or misspellings to correctly score retrieved memory items, an automated one-to-one matching program may not score these items correctly unless a sufficient degree of flexibility is programmed into the scoring package. Instead, *lrd* takes a *fuzzy string matching* approach in which response strings are counted as correct if they closely approximate the key rather than match it exactly (see Singla & Garg, 2012, for review).

By using fuzzy string matching, the functions comprising the *lrd* package have been specifically designed to accurately score lexical text data while granting increased flexibility for minor errors that may be present in recall output, as determined by the user. The goal of this article is two-fold. First, we provide brief overviews of each function contained in both the *lrd* package in the *R* environment and detail the corresponding *R Shiny* application by providing step-by-step guides on how to implement each of these tools to process several types of recall data. Second, we test the accuracy and reliability of the scoring algorithm by comparing output obtained from this package with human coded data using four large data sets. Specifically, we test this package’s reliability by using its scoring functions to recode cued-recall data derived from two recent cued-recall studies (Maxwell & Buchanan, 2020; Maxwell & Huff, 2021), a study employing a free-recall task (Huff et al., 2018), and a study using sentence-recall task (Geller et al., 2020). For each study, we then compare data processed using *lrd* to the findings in the original human coded datasets and tested whether the original findings reported in these studies replicate using *lrd*. By including functions for multiple recall test types, *lrd* can be applied to a wide variety of memory studies. Additionally, this allowed us to assess whether scoring accuracy changes as a function of test type.

For the two cued-recall studies, participants studied lists of paired associates and judged either how related the words in each pair were (Maxwell & Buchanan, 2020) or how likely they would remember the second word if cued by the first at test using a judgment of learning (JOL) rating (Maxwell & Huff, 2021). Upon conclusion of the study/judgment tasks, participants completed a distractor task followed by a cued-recall task in which the first word in each pair was presented and participants were asked to respond with the item it was originally paired with (e.g., *mouse* - ?). Next, for the free-recall data derived from Huff et al. (2018), participants studied six word lists in which list items were either semantically related or unrelated. Following study of each list, participants then engaged in a free-recall task. Finally, for the sentence data taken from Geller et al. (2020), participants listened to a sentence and, following the conclusion of each audio presentation, were instructed to type as much of the sentence as they recalled hearing. The recall data reported in each of the above studies was initially scored by manually checking responses against a scoring key via human coders. We rescored this output using *lrd* to illustrate that output generated automatically from this package is able to replicate human scored results across each recall paradigm with a high degree of precision.

**Overview of the *lrd* Package**

*lrd* is an open-source tool developed for the *R* environment and an interactive application that consists of three basic functions for scoring lexical recall data and assessing the output. This package’s primary goal is to automate the scoring process by matching participant responses to a list of correct responses stored in a key. Critically, this package has been designed to accomplish this task while granting flexibility towards participant response errors (e.g., misspellings or incorrect tenses). We additionally provide functions for specific analyses tied to free-recall data including serial position curves, conditional response probabilities, and probability of first recall (Kahana, 1996; Wahlheim & Huff, 2015).

We begin by providing a set of general instructions for downloading and installing the *lrd* package within the *R* environment. Next, we provide examples of the scoring functions for three types of recall as well as a set of functions that can be used to compute recall proportions for each test type. Third, we provide a general guide on how to use the package within both the *R* environment and through the use of a graphical user interface (GUI) implemented in *Shiny* and *shinydashboard* (Chang et al., 2021; Chang & Ribeiro, 2018). Finally, we conclude by assessing the validity of this package by using the cued-recall, free-recall, and sentence-scoring functions to process sets of each data type that have been scored by human coders.

**Installation and Set Up**

The latest version of *lrd* (including all applicable documentation and source code for each function) can be accessed via GitHub (https://github.com/npm27/lrd). While proficiency with *R* is not required to run this package, it is assumed that users will have some familiarity with the *R* environment and/or basic experience with object-oriented programming. Installation is relatively straightforward, but currently requires the use of the *devtools* package (Wickham et al., 2020) to download and install the files from GitHub. Typing the following command, devtools::install\_github('npm27/lrd') will begin the installation process by downloading and installing the latest version of *lrd*. By providing this package via GitHub, researchers can contribute, fork (i.e., make a copy), and modify functions of this package as needed. Installation using *devtools* will always be supported, and updated installation instructions will be provided when applicable on the README for the package. To begin using *lrd*, be sure to first load the package by using library(lrd). Each function has been documented with information about the arguments and outputs stored within that function. Use ?function name to view the documentation and examples provided within the *R* working environment (i.e., ?prop\_correct\_cued). Several example datasets are also provided within the package to demonstrate the three main scoring functions.

**Cued-Recall Scoring Functions Example**

In this section, we provide a general guide to using *lrd* to score cued-recall data. This example uses a set of simulated response data that were designed to mimic output that might be obtained from a cued-recall study. While the dataset is smaller than what is typically generated from psychological experiments, we note that this set of responses is sufficient for our purpose of illustrating how *lrd* scores participant ouput. We begin this section by detailing the creation of this dataset before providing a step-by-step walkthrough of the *lrd* package’s cued-recall scoring functions. Code and data for all examples have been made available at https://osf.io/admyx/ and within the packages as vignettes.

**Materials and Dataset Creation**

To simulate a set of cued-recall data, forty words were randomly generated using *LexOPS* (Taylor et al., 2020) to serve as target items (i.e., the scoring key containing correct responses). To simplify the stimuli selection process, we followed the general example provided by Taylor et al. by controlling for word prevalence and concreteness when generating this set of items. First, only highly concrete words were included (concreteness ≥ 4, Brysbaert et al., 2014). Pairs were then evenly split based on word prevalence (e.g., the proportion of individuals who are familiar with a word, Brysbaert et al., 2019). Thus, the final stimuli consisted of 20 concrete, high prevalence words (i.e., prevalence ≥ 4) and 20 concrete, low prevalence words (i.e., prevalence ≤ 2).

We next simulated six sets of participant responses to these items. These response simulations varied in their degree of accuracy to cover a broad spectrum of potential participant responses, including no response errors (Participant 1), minor misspellings (Participants 2, 3, and 4), and major response errors (e.g., blank responses, incorrect answers, misspellings of more than two letters; Participants 5 and 6). For Participant 1, all responses matched the key to simulate a situation in which a participant correctly recalls all items. Data for Participants 2 and 3 was manipulated to simulate situations in which participants make minor mistakes at recall that do not necessarily preclude their responses from being counted as correct (e.g., misspellings where it is evident what the intended word is). These were generated by removing, replacing, or doubling specific letters. As such, the letter *e* was removed from all responses for subject 2 (e.g., *hey* becomes *hy*). For Participant 3, all instances of the letter *t* were doubled (e.g., *edit* becomes *editt*). Next, for Participant 4, all instances of the letter *a* were replaced with an *e*. This procedure allowed us to simulate a range of common participant errors such as omitting a letter, typing the wrong letter, or double pressing a key by mistake. Finally, data for Participants 5 and 6 were manipulated to simulate situations in which participants make major mistakes on recall (e.g., responding with an incorrect word). To simulate this type of response error for Participant 5, five responses from the answer key were randomly changed to a different but conceptually similar word (e.g., *financial* becomes *money*). The simulated data for Participant 6 increased the number of incorrect responses and added three instances of missing data.

**Formatting and Loading the Dataset**

To view this example in the package, use vignette("Cued\_Recall", package = "lrd")to load the script and output in one file. When processing data, *lrd* requires that the input data is arranged in long format, wherein each row is one trial of participant responses. The package includes a function to convert wide format data (i.e., one row per participant), and an example of the data conversion is shown in the free-recall section below. We can use the following code to load and view the first six rows of the data[[1]](#footnote-1):

> library(lrd)

> data("cued\_recall\_manuscript")

> head(cued\_recall\_manuscript)

Sub.ID Trial\_num Cue Target Answer

1 1 1 chlorination ideological ideological

2 1 2 bendy financial financial

3 1 3 topography editing editing

4 1 4 enquiry buzzing buzzing

5 1 5 draconian statistic statistic

6 1 6 speedball stopwatch stopwatch

The following information is required to analyze cued-recall data with the corresponding column name in this example in parentheses: a unique identifier for each participant (Sub.ID), a participant response column (Answer), and a unique identifier for each tested item (e.g., such as a trial number, Trial\_num). Additionally, this function requires an answer key containing the correct responses and a unique identifier for each key item; however, these columns can either be stored as part of the input data or may be stored in a separate dataframe. The cued-recall dataframe may contain additional columns (e.g., columns denoting experimental conditions) that can be used to group the output. These columns must be between-subject values to be included in the output, with a one-to-one match between participant identifier and column information. Because scoring is case sensitive, the response and answer key columns will need to be checked for case discrepancies. For simplicity, we suggest converting both the answer key and response columns to lowercase before scoring the data.

> cued\_recall\_manuscript$Target <- tolower(cued\_recall\_manuscript$Target)

> cued\_recall\_manuscript$Answer <- tolower(cued\_recall\_manuscript$Answer)

**Scoring Cued-Recall Data**

Scoring cued-recall data with *lrd* is a relatively straightforward process with the ability to tweak the analysis to different desired outputs. We will run the prop\_correct\_cued() and save the output as a new object (cued\_output).

> cued\_output <- prop\_correct\_cued(data = cued\_recall\_manuscript,

+ responses = "Answer",

+ key = "Target",

+ key.trial = "Trial\_num",

+ id = "Sub.ID",

+ id.trial = "Trial\_num",

+ cutoff = 1,

+ flag = TRUE,

+ group.by = NULL)

>

The data argument should list the dataframe of the participant answers. The responses argument indicates the column to find the participant answer, while the key column indicates the expected answer for that trial. The columns are listed in quotes if they are in the same dataframe as the data argument; however, the answer key columns could be listed in another dataframe to match to the participant answers (i.e., answer\_key$Target). The key.trial and id.trial arguments indicate how to match the answer key trial numbers to the participant data trial numbers. The id argument indicates the participant unique identifier. The cutoff column indicates the Levenshtein distance used for scoring, wherein 0 indicates a perfect answer to key match, and non-zero numbers indicate the number of substitutions, deletions, or changes allowed to consider for matching (Levenshtein, 1966). Levenshtein distance provides a method of fuzzy string matching wherein distance values represent the number of character changes required to transform the first word into the second. For example, two identical words such as *cat* and *cat* would have distance of 0, while *cat* and *bat* would have a distance of 1, and *cat* and *dog* would have a distance of 3. Levenshtein distances are sensitive to changes in character order, which provides an advantage over simple character matching, as *bear* and *bare* would be computed as 100% matching, but a Levenshtein distance score of 3. Given our data simulation, we used a cutoff score of 1 in this example to demonstrate how *lrd* can capture simple misspellings. The flag argument can be set to TRUE to provide the *z*-score values for each participant for their final cued-recall score. Last, the group.by argument is used to include grouping variables to calculate percent recall by group or condition, and more than one variable can be used by concatenating a vector of column names (i.e., c("column1", "column2")).

This function provides up to three pieces of output stored in list format. First, this function provides trial level data showing participant responses to each test item, the corresponding answer key item, and whether the program scored the response as correct (denoted as 1 for correct, 0 for incorrect):

> cued\_output$DF\_Scored

Trial.ID Sub.ID Cue Target Responses Answer Scored

1 1 1 chlorination ideological ideological ideological 1

2 1 3 chlorination ideological ideological ideological 1

3 1 5 chlorination ideological ideological ideological 1

4 1 2 chlorination ideological idological ideological 1

5 1 4 chlorination ideological ideologicel ideological 1

6 1 6 chlorination ideological ideological 0

The second output consists of participant level data, summarizing the proportion correct for each participant and the optional *z*-score for outlier detection:

> cued\_output$DF\_Participant

Sub.ID Proportion.Correct Z.Score.Participant

1 1 1.00 1.0259784

2 2 0.80 0.0000000

3 3 0.85 0.2564946

4 4 0.95 0.7694838

5 5 0.75 -0.2564946

6 6 0.45 -1.7954621

The last output includes statistics of the grouping conditions, if they were included in the scoring function. An example of this output is included below.

**Free-Recall Scoring Functions Example**

The next section provides a general guide for using *lrd* to score free-recall data. For this example, we simulated a set of free-recall responses. The sample data was modeled after output obtained by Gretz and Huff (2019) in which participants watched videos of either healthy or sick individuals interacting with a variety of household objects and were presented with a free-recall test. First, we by detail the creation of this dataset. We then provide a detailed walkthrough of the *lrd* package’s free-recall scoring function.

**Materials and Dataset Creation**

To simulate a set of free-recall data, a list of 22 common household objects was first generated. This list was based on the “bedroom” video used by Gretz and Huff (2019), which can be viewed at https://osf.io/qbrgm/. Next, to simulate a set of responses, data was generated for six participants. To capture response variability, we varied the number of responses each participant provided, spelling errors of correct items, and inclusion of incorrect items. The full sample dataset and answer key files as well as all code used in the following examples have been made available at https://osf.io/admyx/. You can use vignette("Free\_Recall", package = "lrd")to view this example within the package.

**Formatting and Loading the Dataset**

In this example, we will load a free-recall dataset using data(wide\_data) and the answer key for the free-recall lists with data(answer\_key\_free). The dataset is structured in wide format, such that each participant is the one row in the data frame:

> head(wide\_data)

|  |  |  |
| --- | --- | --- |
| Sub.ID | Response | Disease.Condition |
| 1 | basket, chair, clothes, flowrs, glasses, fan, windows, … | healthy |
| 2 | windows, bed, books, shelf, pictures | healthy |
| 3 | bacpack, chair, glasses, mirror, iphone, pillow, … | healthy |
| 4 | vase, blinds, computer, magazine, books, bed, blanket, … | sick |
| 5 | bed, blankets, closet, windows, books, fan | sick |
| 6 | bed, blankets, dreser, nightstand, end table, stereo, … | sick |

For all scoring functions, the data should be converted to long format, which includes one trial per row to properly match the answer key to the answer for each trial. In the example above, the Response column includes all the answers a participant listed using a comma-separated format. If the data is structured so that each concept is in a separate column, the data can be restructured into long format several ways: *reshape* (Wickham, 2007) or *data.table* (Dowle & Srinivasan, 2020) using the melt() function or *tidyverse* (Wickham et al., 2019) using the pivot\_longer()function. In *lrd*, the arrange\_data() function was added to assist in reformatting participants answers that were entered as one text string. To convert the wide\_data into a useable long format, use:

> DF\_long <- arrange\_data(data = wide\_data,

+ responses = "Response",

+ sep = ",",

+ id = "Sub.ID")

The data argument indicates the dataframe containing the variables defined in the next arguments. The column name of the responses is denoted in quotes for the responses argument, and the sep argument indicates the separator between responses (i.e., a comma, semicolon, space, tab, or other text delimitator). The id variable is a column name in the dataframe for the unique participant identifier. Our new dataframe DF\_long will then be converted to long format:

> head(DF\_long)

Sub.ID response position Disease.Condition

1 1 basket 1 healthy

2 1 chair 2 healthy

3 1 clothes 3 healthy

4 1 flowrs 4 healthy

5 1 glasses 5 healthy

6 1 fan 6 healthy

This function first splits the original response column by the separator, strips out additional whitespaces (i.e., two or more spaces become one between tokens), and trims whitespace characters before and after the token(s). The position column is added to denote the order of responses for each participant, and the unique identifier for each participant is repeated for each of their answers. The last component of this function is that all between-subject columns will be added back into the restructured dataframe, provided they have a one-to-one match with the participant identifier. In this example, the Disease.Condition variable is included because each participant was only assigned into one of the groups. If there are multiple trials or conditions for free responses, they should be separated into different dataframes and this process repeated for each trial-answer key pairing.

The answer key is structured as a dataframe with one column of information (shown below). However, the answer key can also be imported by simply typing the answers as a single vector using the concatenate function c().

> head(answer\_key\_free)

Answer\_Key

1 backpack

2 basket

3 bed

4 blanket

5 blinds

6 books

As with cued-recall scoring, the free-recall functions are case sensitive and cannot process missing responses. As such, we again recommend converting both the answer key and response columns to lowercase.

**Scoring Free-Recall Data**

With the restructured data and answer key, the prop\_correct\_free() function can be used to score the free-recall data. This function will compare the answer key to the response column created above, and therefore, each trial of free-recall responses should be analyzed separately.

> free\_output <- prop\_correct\_free(data = DF\_long,

+ responses = "response",

+ key = answer\_key\_free$Answer\_Key,

+ id = "Sub.ID",

+ cutoff = 1,

+ flag = TRUE,

+ group.by = "Disease.Condition")

The arguments for this function are the same as the prop\_correct\_cued() function, minus the trial arguments for matching individual trials, as each trial should be analyzed separately. It is important to note that a non-space delimiter should be used, as spaces may interfere with multiple word tokens (i.e., picture frame is one correctly recalled concept in the answer key). We can then view the separate outputs by printing out the overall dataframe scored:

> free\_output$DF\_Scored

Responses Sub.ID position Disease.Condition Answer Scored

1 bacpack 3 1 healthy backpack 1

2 basket 1 1 healthy basket 1

3 bed 2 2 healthy bed 1

4 bed 4 6 sick bed 1

5 bed 5 1 sick bed 1

6 bed 6 1 sick bed 1

This dataframe can also be used to ensure that the answers appear to match the appropriate target word, as two target concepts that are within one substitution of each other may present scoring issues within this framework (i.e., if the answer list included both *bed* and *bet*). In this example, we included a group.by argument, and therefore, the participant data shows the grouping variable and calculates the *z*-scores for both participants overall (Z.Score.Participant) and within their own group (Z.Score.Group):

> free\_output$DF\_Participant

Disease.Condition Sub.ID Proportion.Correct Z.Score.Group Z.Score.Participant

1 healthy 1 0.3928571 0.5773503 1.0819232

2 healthy 2 0.1428571 -1.1547005 -1.3096965

3 healthy 3 0.3928571 0.5773503 1.0819232

4 sick 4 0.3214286 1.1547005 0.3986033

5 sick 5 0.2142857 -0.5773503 -0.6263766

6 sick 6 0.2142857 -0.5773503 -0.6263766

Last, we find a group summary of mean, standard deviation, and sample size by using:

> free\_output$DF\_Group

Disease.Condition Mean SD N

1 healthy 0.3095238 0.14433757 3

2 sick 0.2500000 0.06185896 3

**Scoring Free-Recall Responses from Multiple Lists**

Although prop\_correct\_free() was designed for scoring output from free-recall studies, it is primarily limited to research designs in which all participants study items taken from a single list. While this function can still be used in situations where participants (or groups of participants) study different lists and in designs where participants are presented with multiple study lists, prop\_correct\_free() requires that the data first be subset by list type, with each list scored separately. This approach, however, quickly becomes tedious as the number of individual groups increases and is further complicated when each group contains multiple counterbalances. As such, prop\_correct\_multiple() can be used to score free-recall responses when participants/groups study multiple sets of lists, regardless of whether all participants study the same list. This function requires the same basic inputs as prop\_correct\_free(). Specifically, the input data must be a dataframe in long format, and the user must specify which dataframe columns contain the participant responses, the answer key, and the participant identifier. In addition, prop\_correct\_multiple() also requires a list identifier (i.e., a unique value denoting which list response items and key items belong to). Thus, both your dataset and answer key will require additional columns denoting this information. While key information can be either character strings or numeric, the values must match between the dataset and the key. These columns can be specified using the key.trial and id.trial arguments for answer key and input data columns, respectively. For a complete example in *R*, use vignette(“Multi\_Recall”, package = lrd).

**Calculating Serial-Position Based Measures in Free-Recall**

The order of the answer key can be used to calculate serial position estimates, conditional response probabilities, and probability of first recall. Serial-position analyses compute proportions of correct recall as a function of the list position presented at study and are often used to plot serial-position curves wherein participants are more likely to remember the first and last items of a list best (Murdock, 1962). Lag-conditional response probabilities (lag-CRPs), compute probabilities for correctly recalled items conditionalized on the distance (i.e., lag) between items presented at study (Kahana, 1996; Kahana et al., 2002). Typically, lag-CRPs indicate that recall is highest at adjacent lags (+1 and -1) and lowest for more distant lags. For instance, if an item from list position 4 is recalled, recall from adjacent positions (3 and 5) is more likely than from more distant positions. Finally, probability of first recall (PFR) refers to the recall probability of the first recalled item from each study set as a function of the studied list position. PFRs typically indicate greater recall from late position items on immediate tests (recency effect), but greater recall for early position items if the test is delayed (primacy effect; Wahlheim & Huff, 2015). For each of these functions, the output from free\_output$DF\_Scored is the expected input. Vignette “Free\_Recall” contains examples for plotting each function with ggplot2.

To create a dataframe of the percent correct by serial position, we can use the serial\_position() function:

> serial\_output <- serial\_position(data = free\_output$DF\_Scored,

+ key = answer\_key\_free$Answer\_Key,

+ position = "position",

+ scored = "Scored",

+ answer = "Answer",

+ group.by = "Disease.Condition")

> head(serial\_output)

Disease.Condition Tested.Position Freq Proportion.Correct SE

1 healthy 1 1 0.3333333 0.2721655

2 healthy 2 1 0.3333333 0.2721655

3 healthy 3 1 0.3333333 0.2721655

4 sick 3 0 0.0000000 0.0000000

5 sick 4 0 0.0000000 0.0000000

6 sick 5 0 0.0000000 0.0000000

In the function, you use similar arguments as our previous examples. The data is likely a dataframe processed from the free-recall functions. The key column represents the ordered answer key. The position argument denotes the position the participant listed each answer, while the scored argument indicates the 0 or 1 denoting whether the answer was scored correct. Last, you can include grouping variables with the group.by argument. The output is shown next, which returns information about the grouping conditions (if included), the position a word was tested (Tested.Position), the total number of times the word was correctly indicated within the acceptable position window (Freq), the proportion correct (i.e., sum divided by participants, Proportion.Correct), and the standard error (SE). Items are added to the Sum column if they are scored as correct and are listed within one item lag of the original tested position (i.e., item 10 would be correct in position 9 or 11), except for the first and last item, which are only considered correct listed as first or last. These data can be used to create a serial position curve visualization or further descriptive statistic calculations based on researcher interest. Similar outputs for conditional response probabilities using the crp() function:

> crp\_output <- crp(data = free\_output$DF\_Scored,

+ key = answer\_key\_free$Answer\_Key,

+ position = "position",

+ scored = "Scored",

+ answer = "Answer",

+ id = "Sub.ID")

> crp\_output[c(28:54), ]

Sub.ID participant\_lags Freq Possible.Freq Disease.Condition CRP

28 1 1 1 8 healthy 0.1250000

29 1 2 1 9 healthy 0.1111111

30 1 3 1 9 healthy 0.1111111

31 1 4 1 9 healthy 0.1111111

32 1 5 1 9 healthy 0.1111111

33 1 6 1 9 healthy 0.1111111

34 1 7 0 0 healthy 0.0000000

35 1 8 0 0 healthy 0.0000000

36 1 9 0 0 healthy 0.0000000

37 1 10 1 8 healthy 0.1250000

38 1 11 0 0 healthy 0.0000000

39 1 12 0 0 healthy 0.0000000

40 1 13 0 0 healthy 0.0000000

41 1 14 1 5 healthy 0.2000000

42 1 15 0 0 healthy 0.0000000

43 1 16 0 0 healthy 0.0000000

44 1 17 0 0 healthy 0.0000000

45 1 18 0 0 healthy 0.0000000

46 1 19 0 0 healthy 0.0000000

47 1 20 0 0 healthy 0.0000000

48 1 21 0 0 healthy 0.0000000

49 1 22 0 0 healthy 0.0000000

50 1 23 0 0 healthy 0.0000000

51 1 24 0 0 healthy 0.0000000

52 1 25 0 0 healthy 0.0000000

53 1 26 0 0 healthy 0.0000000

54 1 27 0 0 healthy 0.0000000

The above example displays crp values across all positive lags for participant 1 (note that this function also returns negative lags, but for concision, they have been omitted from this example). Each lag between subsequent named items is tallied and then divided by the possible combinations of subsequent lags given their response patterns. Therefore, the column participant\_lags represents the lag between the studied position and the test position the item is recalled (e.g., *chair* was reported in the second position on the test, which represents a lag of 6 from spot number 8 on the answer key list which corresponds to the studied order). The column Freq represents the frequency of the lags between listed and shown position, while the Possible.Freq column indicates the number of times that frequency could occur given each answer listed (e.g., given the current answer, a tally of the possible lags that could still occur). The CRP column calculates the conditional response probability, or the frequency column divided by the possible frequencies of lags. Given that conditional response probability is calculated by participant, there is no group.by argument; however, the columns are returned as part of the dataframe for further analysis if desired. Last, we provide calculations for the probability of first response:

> pfr\_output <- pfr(data = free\_output$DF\_Scored,

+ key = answer\_key\_free$Answer\_Key,

+ position = "position",

+ scored = "Scored",

+ answer = "Answer",

+ id = "Sub.ID",

+ group.by = "Disease.Condition")

> head(pfr\_output)

Tested.Position Disease.Condition Freq pfr

1 1 healthy 1 0.3333333

2 2 healthy 1 0.3333333

3 3 healthy 0 0.0000000

4 27 healthy 0 0.0000000

5 28 healthy 1 0.3333333

6 1 sick 0 0.0000000

Participant answers are first filtered for their first response, and these are matched to the original order on the answer key list (Tested.Position). Then the frequency (Freq) of each of those answers is tallied and divided by the number of participants overall or by group if the group.by argument is included (pfr). Each of these functions can be used to calculate further statistics or create visualizations, and the included *Shiny* application automatically displays basic visualizations of these functions as part of the free-recall output.

**Sentence Scoring Function Example**

In addition to scoring cued-recall and free-recall responses, *lrd* can also be used to score the match between two sentences. In this section, we provide a general overview of using *lrd* to score sentences. This example uses a set of simulated sentence responses generated for six participants. We begin this section by detailing the creation of this dataset. We then provide a detailed walkthrough of the *lrd* package’s sentence processing functionality.

**Materials and Dataset Creation**

To simulate a set of sentence responses, we first generated a list of five simple sentences to serve as the answer key. Next, to simulate a set of responses, sample data was generated for six participants, leading to a total of 30 observations. To capture response variability, we varied the amount of error within each response, such that some sentences included spelling errors, inclusion of extra words, omission of words, and/or semantically similar words. The full sample dataset and all code used in the following example has been made available at https://osf.io/admyx/.

**Formatting and Loading the Dataset**

To view this example in *R*, use vignette("Sentence\_Recall", package = "lrd"). As with our cued-recall example, the data will need a participant identifier, a trial identifier, the answer key, the participant’s answer, and any other grouping columns that may be present. The answer key can be stored separately from the participant answers, as the trial identifier will be used to merge them together. Unless sentence case is part of the requirements for the study, we would recommend normalizing all text to lowercase. In our example below, we simulated extra whitespaces that participants may use, which will be eliminated as part of the scoring function.

|  |  |  |  |
| --- | --- | --- | --- |
| 1 | Sub.ID Trial.ID | Sentence | Response Condition |
| 2 | 1 1 | This is a sentence. | This is a sentence. a |
| 3 | 1 2 | Woo more sentences! | Woo more sentences! a |
| 4 | 1 3 | This is the thing the participant typed. | This is thing the participant typed. a |
| 5 | 1 4 | This is another example sentence. | This is another example sentence a |
| 6 | 1 5 | Okay this is the final thing that they typed. | Okay this is the final thing they typed. a |
| 7 | 2 1 | This is a sentence. | This is sentence. b |

**Scoring Sentence Data**

To score sentence data with *lrd*, begin by running prop\_correct\_sentence()and save the output as a new object. This function follows the same general format as the cued- and free-recall scoring functions. You should specify the dataframe (data), the columns containing the participant responses (responses), the answer key (key), the participant identifier (id), and the trial identifiers (id.trial, key.trial). Each token will be scored individually against the target answer, and the cutoff indicates the allowable Levenshtein distance. Again, you can flag outliers by participant and/or grouping variable (group.by). The token.split argument is used to specify the character that separates words in each sentence, and the default is a single space.

> sentence\_ouptut <- prop\_correct\_sentence(data = sentence\_data,

+ responses = "Response",

+ key = "Sentence",

+ key.trial = "Trial.ID",

+ id = "Sub.ID",

+ id.trial = "Trial.ID",

+ cutoff = 1,

+ flag = TRUE,

+ group.by = "Condition",

+ token.split = " ")

The overall output contains the scoring for each participant and item. The entire output can be viewed on our vignette, and for our example here, we display the new columns that are added to the dataframe and a few rows with specific examples of the issues one might encounter when scoring sentences.

> sentence\_ouptut$DF\_Scored

Proportion.Match Shared.Items Corrected.Items Omitted.Items Extra.Items

2 0.7500000 this is sentence <NA> a <NA>

19 0.8000000 this is example sentence <NA> another an extra

24 0.6000000 this is another <NA> example sentence one

29 0.4444444 this is final th okay thing that typed one

22 1.0000000 is another sentence tis xample <NA> <NA>

10 1.0000000 woo more sentences <NA> <NA> <NA>

First, each sentence is stripped of punctuation and extra white space within the function. The total number of tokens, as split by token.split are tallied for calculating Proportion.Match. Then, the tokens are matched using the Levenshtein distance indicated in cutoff, as with the cued and free-recall functions. The key difference in this function is how each type of token is handled. The Shared.Items column includes all the items that were matched completely with the original answer (i.e., a cutoff of 0). The tokens not matched in the participant answer are then compared to the tokens not matched from the answer key to create the Corrected.Items column. This column indicates answers that were misspelled but within the cutoff score and were matched to the answer key (i.e., *th* for *the*, *ths* for *this*). The non-matched items are then separated into Omitted.Items (i.e., items in the answer key not found in the participant answer), and Extra.Items (i.e., items found in the participant answer that were not found in the answer key). The Proportion.Match is calculated by summing the number of tokens matched in Shared.Items and Corrected.Items and dividing by the total number of tokens in the answer key. Both sentence\_ouptut$DF\_Participant and sentence\_ouptut$DF\_Group can be used to view output that has the same information as shown in the cued- and free-recall sections for participant and group summaries of proportion correct.

**R Shiny Application**

While *lrd* was initially designed as a package to be used within the *R* command environment, we recognized the need for an easy to access option that can be used independent of *R*. As such, we have developed a *Shiny* application that provides researchers with a programming-free alternative to using this tool that can be operated using basic Excel skills. Furthermore, because this application is web based (available at https://npm27.shinyapps.io/lrd\_shiny/), no software downloads are required. The *lrd* *Shiny* application is structured as a series of tabs. Upon opening the application, you will be directed to the Information Tab (see Figure 1). From here, the menu on the left can be used to navigate to the appropriate scoring task. Selecting a task will open a new tab in which the data and answer key can be uploaded, and other parameters can be set. For all scoring tasks, data will need to be structured in long-format, and the Arrange Data tab can be used prior to scoring to first convert wide-format data into the appropriate format. Additionally, each of the three scoring tabs provides options for downloading scored output for use in *R*, SPSS, Excel, or other programs. In the following sections, we provide detailed explanations for each of the three scoring tabs.

**Cued-Recall Tab**

When using the *Shiny* application to score cued-recall data, the uploaded dataset needs to be arranged in long format and must contain the following columns: A unique participant identifier, participant responses, and a trial number for each recall trial. Additionally, cued-recall scoring requires an answer key and trial identifier for each key item (such as a trial number). If the answer key is embedded in the original participant data, simply upload the participant data in the answer file section. Finally, the dataset being scored may contain other columns (e.g., such as those denoting experimental conditions, demographics, etc.), which can be selected using the “group by” option. Figure 2 (top panel) displays the cued-recall tab following data upload. The Check Your Data box can be used to determine that the data was uploaded correctly. The *rio* library is used to import data and generally provides a correct interpretation of the data, but errors can occur, generally with data that does not have a clear column header row (Becker et al., 2021).

After uploading both the dataset and answer key, the Scoring Set Up box can be used to indicate the columns for each relevant argument, the scoring cutoff, and the ability to provide *z*-scores for outliers. Like the *R* package, the scoring denotes the Levenshtein distance between the participant response and key item and represents the total number of insertions, deletions, and substitutions one might need to convert the given response to the answer key. Therefore, a selection of 1 represents a one letter difference between the response item and the key, while a selection 5 represents 5 changes.

Once the appropriate settings have been selected, clicking “Score Your Data” will begin the scoring process. Scored output will then be displayed in the Scored Output box located below the data upload panel corresponding to the DF\_Scored information from the *R* function (See Figure 2 bottom panel). Next, the Summarized Output box displays the participant dataframe with the correct recall proportions. If a grouping variable was selected, recall proportions at the group level will also be displayed. Finally, the bottom panel displays recall proportions plotted as a function of the grouping variable. If no grouping variable is selected, this panel will display a histogram of recall proportion. At the top of each dataframe output, a set of buttons can be used: Copy for simple cut and paste of the dataframe, CSV for comma separated download, or Excel for .xlsx download. Graphs can be saved by right clicking to save or copy the graph, but unfortunately, they cannot be edited within the app.

**Free-Recall Tab**

As with cued-recall scoring, free-recall data will also need to be uploaded in long-format. For simplicity, we suggest uploading the response data and answer key as two separate files. First, the participant response data will need to contain at minimum the responses and a unique participant identifier, along with grouping variables if desired. Next, the answer key file should at least contain one column of answers ordered by serial position. Free-recall data is then scored using the same general procedure as cued-recall. Use the Scoring Set Up box denote the appropriate columns for each argument, select a cut-off score, and flag for outliers. If the upload data contains a column denoting the order in which items were recalled, this column can be selected using the “position answered” box and will be used for creating serial position curves, lag-CRPs, and PFRs. Note that this column is automatically generated if the Arrange Data tab is used to convert the upload data from wide to long-format (Figure 3). The scored dataset is then previewed in the Scored Output box, along with the Summarized Output box at the participant and grouping levels (Figure 4). A graph of the free-recall proportions will be created as a function of the grouping variable(s) selected or a histogram of participant level responses. The last three boxes include the serial position, lag-CRP, and PFR dataframes for download and their corresponding plots for visualization.

[MULTIPLE TAB]

[WORDS HERE]

**Sentence-Recall Tab**

When scoring sentence-recall, the data upload process closely follows cued-recall data scoring. The data will need to be arranged in long-format such that each row corresponds to one participant response. Moreover, the response column should be structured such that each cell contains the full participant response (i.e., each cell in the response column contains a full sentence). Example data illustrating the format required for the upload data is available at: https://osf.io/mcg9f/. Finally, this data will need to contain each of the necessary columns from the cued-recall tab. The answer key can either be included as a column with the upload data or it can be uploaded as a separate file. When scoring sentence data, in addition to selecting the cutoff criteria, you will need to select the delimiter for sentence tokens (i.e., the character(s) separating each word within the sentences). The token delimiter can be typed into the box below the scoring cutoff selection, and the default is a single space. If a different character separates words, you will need to delete this space before typing a different character.

After scoring, the Scored Output box can be used to preview the final dataset. In addition to showing whether the sentence was correctly recalled, this panel will also return any tokens omitted from the answer key and any extra words included in the response (see Figure 5). Next, the Summarized Output box displays participant level and group level (if specified) recall proportions. Finally, plots can be viewed via the graph box located at the bottom of this tab.

**Validation of Scoring Functions**

We now turn to set of analyses designed to validate *lrd* package’s scoring functions by using *lrd* to score cued-recall, free-recall, and sentence-recall datasets and comparing the output to human-coded data. For each recall task, we first conducted sensitivity and specificity analyses to determine the optimal Levenshtein distance for scoring before conducting additional analyses to assess accuracy and reliability. These analyses served as additional assessments to ensure that *lrd* can consistently produce accurate scoring across different sets of stimuli. We then tested whether the results of these studies would differ significantly from the original findings after the raw data was processed and scored using *lrd*, allowing us to test the accuracy of this package at the participant level. Finally, we computed Cohen’s *κ* to assess reliability between the different coding sources. We begin this section by testing *lrd*’s ability to score cued-recall data. Subsequent sections test scoring of free-recall and sentence-recall.

**Cued-Recall Scoring Functions Validation**

In this section, we report results from two sets of analyses in which we tested the cued-recall scoring accuracy of *lrd*. First, we use *lrd* to score the datasets used for each set of analyses. These data were derived from two sources: Maxwell and Buchanan (2020) and Maxwell and Huff (2021). We begin by providing details for each dataset, including participant and stimuli characteristics for each study. We then discuss the selection criteria for the Levenshtein distance value used at scoring and detail the results of a set of sensitivity and specificity analyses that were used to test potential cutoff values and provide a step-by-step walkthrough of the scoring process. Finally, we conclude this section by detailing each of the analyses described above.

**Participants and Materials**

Each dataset was collected separately across two different experimental settings. The first set of participants was originally reported in Maxwell and Buchanan (2020; dataset available at https://osf.io/y8h7v/). This dataset consists of 222 participants who were recruited online via Amazon’s Mechanical Turk, a site which allows researchers to access a large pool of participants who complete surveys in exchange for small sums of money (Buhrmester et al., 2011). Next, Maxwell and Huff’s (2021) data consists of 112 undergraduate students who were recruited from a Psychology research pool at a large southern university and tested in lab (dataset available at https://osf.io/hvdma/). These participants completed the study in exchange for partial course credit and were recruited to take part in one of four experiments. For purposes of this paper, we collapsed across experiment to include all 112 subjects in one dataset. Combining datasets across studies resulted in 31,301 recall entries from 334 participants.

Datasets were selected due to their similarity in design. Each study presented participants with paired-associate study lists and later had them complete cued-recall tasks. Furthermore, each study contained reasonably sized samples (all *n*s > 90) and presented participants with at least 60 item pairs to study, providing us with a sufficient number of observations with which to test the reliability of this package. Each study presented participants with a set of cue-target paired associates (e.g., *credit* – *card*). Participants were asked to study each pair before making a judgment of either the pair’s relatedness or their ability to recall the pair at test. After completing the study and judgment tasks, participants then completed a cued-recall test. While participant judgments were collected in each experiment, they are not included in the following analyses as we are only interested in analyzing the accuracy of *lrd* in scoring recall responses.

**Data Processing and Scoring**

To assess the reliability of the cued-recall scoring functions, we first used *lrd* to process and score the two cued-recall datasets introduced above. We then compared output obtained through this scoring process to the original, manually coded output reported in these studies and tested whether the initial findings would replicate. Prior to running the scoring algorithm, .csv files containing participant responses, answer key, trial numbers, and unique identifiers for each participant were created for each of datasets. Data from each study were then scored using the prop\_correct\_cued() function. Scoring was an iterative process which used each of the suggested six Levenshtein distance values (i.e., 0-5). Thus, each dataset was scored six times, once for each scoring criterion, which allowed us to track how changing the Levenshtein distance affected scoring accuracy.

**Determining the Optimal Scoring Criterion**

Given the *lrd* package’s scoring functions work by computing the Levenshtein distance between two strings, we first needed to determine the optimal distance score that would maximize the number of correct hits (e.g., true positives) while simultaneously minimizing the number of false positives and false negatives. To this end, we conducted a set of sensitivity and specificity analyses for each dataset (see Altman & Bland, 1994, for a review) comparing each level of *lrd* scored data to the original, human coded data. Within the context of this study, sensitivity refers to the proportion of true positives that *lrd* correctly identifies (i.e., a participant correctly responds to the cue item with the correct target word and the program correctly identifies it) divided by the true positives plus false negatives (i.e., a miss, when the hand scoring indicates the item was right but *lrd* does not). Specificity refers to the proportion of true negatives identified by the program (i.e., the program correctly identifies that a participant missed an item at test) divided by the true negatives plus the false positives (i.e., *lrd* indicates the item was correct when the hand scoring did not).

Sensitivity and specificity analyses were computed in *R* using the *caret* package (Kuhn, 2008). Table 1 reports sensitivity and specificity percentages for each dataset computed across of the six Levenshtein distance cutoff values. Overall, both datasets displayed a consistent pattern of results: Sensitivity and specificity were each maximized when the scoring cutoff used a Levenshtein distance of 1, suggesting that this value allowed the scoring algorithm to achieve maximum accuracy. We therefore suggest that a Levenshtein distance of 1 provides the optimal cutoff value for minimizing false positives and negatives; however, the program allows researchers to increase or decrease the cutoff value as desired.

**Analyses and Results**

After determining the optimal range of cutoff values to use with the scoring functions, we now turn to a set of analyses that test whether data scored using *lrd* can successfully reproduce the results from each of the original, manually scored datasets. We begin this section by providing descriptive statistics of recall rates for both the original and rescored datasets and then test whether these recall rates differ as a function of coder. Finally, we compute the inter-rater reliability between the human coded and *lrd* scored data. Each dataset was analyzed individually, providing us with two separate tests of the *lrd* package’s scoring accuracy. Generalized-eta squared (*η*2G) and Cohen’s *d* eﬀect sizes are reported for signiﬁcant analyses of variance (ANOVAs) and *t*-tests, respectively. As effect size estimates provide a more useful interpretation of this package’s scoring accuracy, we elected to set significance for analyses at the standard ɑ < .05 level. We note, however, that all significant main effects/interactions hold when using a more stringent ɑ < .001.

**Replication of Cued-Recall Studies**

To test whether cued-recall data scored using *lrd* could successfully replicate human coded data, we conducted two one-way Analysis of Variance (ANOVA) models which tested whether recall cued-rates differed between the 7 scoring types (the 6 *lrd* scoring criteria ranging from 0-5 plus the human coded data). For completeness, means, 95% CI’s, and Cohen’s *d* effect size indices for all comparisons are reported in Tables 2 and 3. Starting with the Maxwell and Buchanan (2020) dataset, a significant effect of scoring type was detected between the human coded data and the *lrd* scored, *F*(6, 1320) = 558.12, *MSE* = 3115.42, *p* < .001, *η*2G = .26. However, post-hoc analyses indicated that this effect was largely driven by differences between the higher Levenshtein distances (i.e., scored using a cutoff of 3 or greater) and the human coded data (*t*s ≥ 3.19, *d*s ≥ 0.29). Recall rates from the *lrd* scored data did not significantly differ from the human coded data (*M* = 54.14) when *lrd* scoring used a Levenshtein distance of 0 (*M* = 50.23), 1 (*M* = 52.14), or 2 (*M* = 53.37; *t*s ≤ 1.23, *p*s ≥ .209).

Next, for the Maxwell and Huff (2021) dataset, an effect of scoring type was also detected, *F*(6, 666) = 1433.93, *MSE* = 14.82, *p* < .001, *η*2G = .53. Post-hoc analyses again showed that this effect was largely driven by differences in mean recall between the human coded data (*M* = 43.96) data that was scored with *lrd* using a Levenshtein distance cutoff of 3 or greater, *t*s ≥ 3.86, *d*s ≥ 0.52. Recall rates did not differ between the human coded data and any of the other *lrd* cutoff points, *t*s ≤ 1.60, *p*s ≥ .110. Thus, using *lrd* to score participant responses did not result in significant changes in outcome across any of the experiments, particularly when an optimized scoring criterion as based on the sensitivity and specificity analyses was used. As such, these findings suggest that *lrd* is able to code cued-recall data equivalently to human coders.

**Inter-Rater Reliability**

To test the inter-rater reliability between the original data and the rescored data, we computed *κ* values for all data sets at the individual trial level. These values were computed in *R* using the *psych* package (Revelle, 2020). The *κ* statistic ranges from -1 to 1, and inter-rater reliability is considered strong if *κ* exceeds .80 (Cohen, 1960). Beginning with the Maxwell and Buchanan (2020) data, a strong agreement was detected between the human coded data and response sets scored using Levenshtein distances of 0, 1, and 2, *κ*s ≥ .96, with this agreement weakening when the data was scored using higher Levenshtein distances. The Maxwell and Huff (2021) dataset showed a similar pattern of agreement between coding methods, with strong agreement for Levenshtein distances less than 3, *κ*s ≥ .94, and weaker agreement when more liberal scoring criteria were used (*κ*s ≤ .85). Table 4 reports individual *κ* statistics for all comparisons within each dataset. Across datasets, reliability between human and *lrd* scored data was highest when a Levenshtein distance of 1 was used, and lowest when scoring used a Levenshtein distance of 5. These results provide further evidence that using *lrd* to score cued-recall responses results in output that is highly consistent with what is produced by human coders.

**Free-Recall Scoring Functions Validation**

We now turn to a set of analyses in which we evaluated the *lrd* package’s ability to accurately score free-recall data. First, we detail the dataset, including all participant and stimuli characteristics. We follow the same general procedure used to validate the cued-recall functions, including the use of sensitivity and specificity analyses to test potential cutoff values and comparing the *lrd* scored output to the original human-coded data as a test of whether the original results can replicate. Finally, we conclude the analyses by computing Cohen’s *κ* to assess reliability between the various coding sources.

**Participants and Materials**

All data used in these analyses was originally published in Experiment 4A of Huff et al. (2018), who recruited 120 participants to complete the study online via Amazon’s Mechanical Turk. Recall was assessed across three types of study lists: Categorical lists in which items were strongly related, ad-hoc lists in which items were weakly related, and unrelated lists. Six lists of 20 items were generated, and participants studied two lists of each type (i.e., 40 of each item type). Following presentation of each list, participants completed a free-recall test. This experiment provided us with 720 individual free-recall tests (120 participants × 6 list presentations). Across tests, participants made a total of 6520 correct responses (out of 14,400 potentially correct responses).

**Data Processing and Scoring**

To assess the reliability of the free-recall scoring functions, we began by generating a scoring key for each of the six lists. Lists were combined by type (ad-hoc, categorical, unrelated) resulting in three unique key lists. Lists were then arranged into long format using the *reshape* package. The final answer key file contained each list along with a “List Type” column denoting whether the key item belonged to the ad-hoc, categorial, or unrelated list. We then used *lrd*’s arrange\_data() function to convert participant responses into long format. Following reshaping of the dataset, we created a “List Type” column denoting which answer key to use for scoring, which corresponded to the “List Type” column in the answer key. The dataset was then scored using prop\_correct\_multiple(). This scoring was an iterative process which used each of the six cutoff values as used in the sensitivity and specificity analyses, allowing us to monitor how changes to the Levenshtein distance selected for scoring affected the scored output. The final dataset was created by combining the scored output at each of the six cutoff values with the original human coded data.

**Determining the Optimal Scoring Criterion**

Before testing whether *lrd* could successfully replicate human coded free-recall data, we again needed to determine the optimal cutoff value for this function that would maximize the number of correct hits (e.g., true positives) while minimizing the number of false positives and false negatives. To do so, we again turn to a series of sensitivity and specificity analyses for each the three datasets. These analyses followed the same design used when validating the cued-recall functions.Table 5 displays sensitivity and specificity percentages for each dataset computed at each of the selected cutoff values. Each of the three datasets displayed a similar pattern of results. Sensitivity and specificity were maximized when the Levenshtein distance was set at either 1 (ad-hoc and categorical lists) or 0 (unrelated lists), though both cutoffs were very similar, indicating that either cutoff would be appropriate. We note, however, that both prop\_correct\_free() and prop\_correct\_multiple() allow this value to be edited as desired, providing users with maximum control over the scoring process.

**Analyses and Results**

We next conducted a series of analyses that tested whether free-recall data scored with *lrd* successfully replicates the results from the original human coded dataset. First, we provide descriptive statistics of recall rates for both the original and rescored datasets. Next, we test whether these recall rates differ as a function of coding. Finally, we conclude this section by computing the inter-rater reliability between the human- and *lrd*-coded datasets.

**Replication of Free-Recall Studies**

First, data from each of the three list types were scored with *lrd* using all 6 Levenshtein distance cutoff values between 0 and 5. Next, three one-way ANOVAs were used to test whether recall rates differed between the seven scoring types (the six *lrd* scoring criteria plus the human coded data) for each of the three study list types. For completeness, means, 95% CI’s and Cohen’s *d* effect size indices for all comparisons are reported in Table 6. Beginning with the categorical list items, no significant differences were detected between the human coded data or the *lrd* scored data at any of the Levenshtein distance cutoff values, *F*(6, 833) = 2.37, *MSE* = 261.02, *p* = .028,  *η*2G = .017. Post-hoc testing, however, indicated that this effect was primarily driven by differences in mean recall between the human coded data and the 0 cutoff (*t*(237) = 1.99, *SEM* = .019, *p* = .048, *d* = 0.25), and differences in scoring between the strict and lenient cutoffs (*t*s ≥ 2.10, *d*s ≥ 0.27). Correct recall did not significantly differ between the human coded data and any of the other *lrd* cutoff points, *t*s ≤ 1.63, *p*s ≥ .105. Furthermore, this pattern failed to extend to the ad-hoc lists, *F*(6, 833) = 1.19, *MSE* = 273.41, *p* = .310,  *η*2G = .008, and the unrelated lists, *F*(6, 833) = 1.40, *MSE* = 294.51, *p* = .269,  *η*2G = .009, as no effect of scoring type was detected. As such, using *lrd* to score free-recall responses did not result in significant changes in outcome across any of the datasets, regardless of whether a strict or lenient scoring criterion was selected. Thus, the results of these analyses indicate that *lrd* can score free-recall data equivalently to human coders.

**Inter-Rater Reliability**

Finally, we computed *κ* values for all data sets at the individual trial level as a test of inter-rater reliability. Starting with the categorical list, a strong agreement was detected between the human coded data and the *lrd* scored data when using each of the six scoring conditions, *κ*s ≥ .89. Next, for the ad-hoc dataset, a strong pattern of agreement was again detected, with agreement being strongest when scoring used cutoffs of 0, 1, and 2 (*κ*s ≥ .90) while strength of agreement decreased when scoring used a cutoff of 3 or greater (*κ*s ≤ .87). Finally, the unrelated list exhibited a pattern similar to the categorical lists, as the agreement observed between the human and *lrd* coded data was strongest when scored using cutoffs of 0, 1, and 2 (*κ*s ≥ .92) and again decreased when using more lenient cutoffs (*κ*s ≤ .87). Table 7 reports individual *κ* statistics for all comparisons between human and *lrd* scored responses within each dataset. Based on the results of these analyses, we suggest using a Levenshtein cutoff of 1 when scoring free-recall responses. Taken together, the results of these analyses provide further evidence that free-recall data scored with *lrd* to is consistent to what is generated by human coders.

**Sentence Scoring Functions Validation**

We now detail a set of analyses which were designed to test *lrd*’s ability to accurately score sentence-recall. We begin by providing a description of the dataset and note that these analyses closely follow the procedure used to validate both the cued- and free-recall functions by testing potential cutoff values for scoring, testing whether the *lrd* scored output can replicate the original human coded data, and assessing the reliability between coding sources.

**Participants and Materials**

Data in the following analyses was originally published as part of Geller et al. (2020) and is available at https://osf.io/ag7nc/. Geller et al. (2020) included 100 participants who listened to 20 sentences taken from AzBio (Spahr et al., 2012), a large, open-set database of recorded sentences. After listening to each sentence, participants were instructed to immediately type each sentence from memory exactly as heard. Typed responses were then manually coded by two independent reviewers, leading to two sets of human coded data (each consisting of 2000 responses) with which to test *lrd*’s sentence scoring functions.

**Data Processing and Scoring**

To test the reliability of this package’s sentence scoring capabilities, we began by using *lrd* to process the dataset described above using each of the six Levenshtein distance cutoffs. Because Geller et al. (2020) scored their output using two independent coders, we treated each coder as a separate dataset. Afterwards, we compared output obtained using *lrd* to each set of manually coded output and tested whether the *lrd*-scored data would replicate the original findings. Before running the scoring algorithm, we generated two .csv files (one for each human coder) containing participant responses, answer key, trial numbers, and unique identifiers for each participant. We then scored each dataset using the prop\_correct\_sentence() function. Consistent with the previous analyses, this scoring process was iterative such that we used each of the six Levenshtein distances. This resulted in each dataset being scored six times, allowing us again to track how changing the cutoff criteria affected scoring accuracy.

**Determining the Optimal Scoring Criterion**

Before scoring the data, we again needed to determine the optimal cutoff value for the sentence-scoring function that would maximize the number of true positives while minimizing the number of false positives and false negatives. To do so, we again turn to a series of sensitivity and specificity analyses, comparing the *lrd* scored data at each Levenshtein distance cutoff to each of the two human coders who originally scored the Geller et al. (2020) dataset. Table 8 displays sensitivity and specificity percentages for each of the six selected values. Overall, sensitivity and specificity were maximized when low Levenshtein distances (≤ 1) were selected, suggesting that these values maximized correct hits while simultaneously limiting false positives and negatives. As such, we propose that a value of 1 be selected when using *lrd* to perform sentence matching as this will provide some correction for minor discrepancies between the key and response (e.g., spelling errors), but note that as with the other scoring functions, this value can be modified as needed to provide flexibility in scoring.

**Analyses and Results**

After determining the optimal cutoff value for scoring, we next conducted a series of analyses testing whether sentence data scored with *lrd* successfully replicates the human coded dataset. We begin this section by providing descriptive statistics for recall rates in both the human and *lrd* scored datasets and test whether these datasets significantly differ as a function of coding source. We then conclude our analyses of the sentence-recall data by assessing the inter-rater reliability between each dataset.

**Replication of Sentence-Recall Studies**

First, data from each of the three list types were scored with *lrd* using all six Levenshtein distance cutoff values between 0 and 5. Next, two one-way ANOVAs were conducted, testing whether recall rates differed between the seven scoring types (the six *lrd* scoring criteria plus the human coded data) for each of the two human coders. Table 9 reports means, 95% CI’s, and Cohen’s *d* effect sizes for all comparisons.

Beginning with data scored by the first human coder, a significant difference was detected between the manually and *lrd* scored data, *F*(6, 594) = 204.37, *MSE* = 22.02, *p* = < .001, *η*2G=.12; however, post-hoc *t*-tests revealed that this effect was largely driven by differences between the human coded data and the data scored with *lrd* using more lenient cutoffs. Specifically, recall rates differed from the human scored data (*M* = 31.80) when a cutoff of 3 (*M* = 40.15), 4 (*M* = 44.55), or 5 (*M* = 46.45) were selected (*t*s ≥ 3.58, *d*s ≥ 0.51). However, the *lrd* scored data did not differ from the human coded data when it was scored using cutoffs of 0 (*M* = 29.10), 1 (*M* = 32.90), or 2 (*M* = 34.25; *t*s ≤ 1.12, *p*s ≥ .265). When compared to the second human coder, an effect of coding source was again detected, *F*(6, 594) = 209.77, *MSE* = 21.89, *p* < .001, *η*2G= .12. This effect largely followed the same patterns as the first human coder such that mean recall rates differed from the human scored data (*M* = 31.30) when *lrd* scoring used cutoffs of 3 or greater (*t*s ≥ 3.75, *d*s ≥ 0.53). However, the *lrd* scored data again did not differ from the human coded data when scored using cutoffs less than 3 (*t*s ≤ 1.33, *p*s ≥ .186). Given the result of this set of analyses, using *lrd* to score sentence-recall did not result in significant changes when scoring used more stringent cutoff values (e.g., using a Levenshtein distance < 3). The results of these analyses suggest that when using the appropriate settings, *lrd* can score sentence responses with similar accuracy to human coders.

**Inter-Rater Reliability**

Finally, we tested the inter-rater between each human coder and *lrd* by computing *κ* values for at the individual trial level. Table 10 reports individual *κ* statistics for all comparisons within each for each of the human coders. Beginning with sentences scored by the first human coder, a strong agreement was detected between the human and *lrd* scored data when a cutoff value of at least 2 was used, *κ*s ≥ .90, and a moderate agreement was found when sentences were scored using a cutoff of 3 or higher, *κ*s ≥ .69. This pattern extended to the second human coder. Again, a strong agreement between the *lrd* and human coded data emerged when a cutoff of at least 2 was used, *κ*s ≥ .91. A moderate agreement was again detected when sentences were scored using a cutoff value of 3 or higher, *κ*s ≥ .69. Thus, based on this set of results of these analyses, we propose using a Levenshtein cutoff of 1 when using *lrd* to score sentence-recall, as this value provided strong agreement between both sets of human coded data while still granting flexibility in participant responses due to minor errors. Given the strong agreement detected by these analyses, sentence data scored with *lrd* to is comparable to output generated by human coders.

**General Discussion**

The goal of *lrd* is to provide researchers with a free, open-source method for quickly and accurately processing lexical output from cued-recall, free-recall, and sentence-recall studies. Across each of these three memory tasks, data scored using *lrd* consistently matched output from human coders reliably and accurately. Importantly, our use of fuzzy string matching via Levenshtein distances provides *lrd* with increased flexibility in scoring compared to direct string matching. Furthermore, because researchers can select from a range of Levenshtein distances when setting up the scoring functions, this flexibility can be adjusted as needed. However, care must be taken when selecting this scoring cutoff, as our analyses showed that findings will change if too lenient (or strict) of a cutoff is used. Thus, an interesting question becomes which cutoff value provides sufficient flexibility to account for common participant errors without being so lenient that blatantly incorrect responses are counted as correct? In general, we encourage researchers to select a stricter cutoff when possible, and our analyses generally support this notion. For example, for both our cued-recall data and sentence-recall datasets, *lrd* most closely matched human coders when scoring was done using a Levenshtein distance of 1. We note, however, that both the type of recall task and the nature of the stimuli will need to be considered when making selecting the cutoff value. This is evident in our free-recall analyses, as scoring of this recall type was most accurate when using a more lenient cutoff of 3. Thus, while we recommend using a cutoff of 1 for cued-recall and sentence-recall designs, and a cutoff of 3 for free-recall designs.

While *lrd* was designed to process lexical output from a wide variety of memory studies, we note that between-subject designs in which each participants are assigned to groups that study different lists will require an extra degree of processing before they can be scored using this package. Because *lrd* assumes that participants were presented with all items in the answer key, participants would first need to be grouped into separate datasets based on the lists they studied, with corresponding answer keys generated that contain only the items studied by a particular group. After creating these subsets and their associated answer keys, scoring can then proceed, with each group being scored separately. Following scoring, the final scored datasets can then be combined to create the final scored output. Should issues regarding various study designs arise, the open-source nature of *lrd* allows for additional functions to be developed as needed.

Finally, while we developed *lrd* to process lexical output from memory studies, we note that recent work in the domain of speech perception has also led to the development of tools for automatically scoring lexical responses. Both the *Autoscore* package for *R* (Borrie et al., 2019) and Bosker’s (in press) application for computing Token Sort Ratio (TSR) provide alternative methods for matching lexical data. Like *lrd*, both *Autoscore* and TSR were designed to speed up the scoring of lexical output from speech perception studies while maintaining the accuracy of a human coder. However, these applications differ from each other and from *lrd* in their general approach to string matching, and that neither program was designed to score lexical output from memory studies. Instead, these tools were developed to assist with matching transcribed audio (typically sentences or phrases) to a key. Thus, while these tools can be used for single-word matching, they are most appropriate for sentence-matching tasks.

Additionally, the *Autoscore* package processes lexical data by assessing whether responses match between a transcript and response, regardless of the order in which response words are generated. Additionally, this program controls for participant errors via a set of hard-coded spelling and grammar rules that are available for the user to select from (e.g., match words based on root words, ignore double letters, etc.). While this rules-based approach can account for a variety of common response errors, it requires researchers to guess which type of errors will be most likely to occur, rather than correcting for errors as they are detected. TSR, on the other hand, uses a fuzzy-matching approach in which the individual tokens (i.e., words) comprising the key and the response are each sorted alphabetically before comparing the match between the two ordered strings (see Bosker, 2021 for an overview).

While both *lrd* and TSR provide means of fuzzy matching, *lrd*’s use of Levenshtein distance is more appropriate the single-word responses that are commonly elicited in memory research. Furthermore, neither *Autoscore* nor TSR were designed to handle open-ended response tasks such as free-recall, in which there is not always a direct one-to-one correspondence between participant responses and answer key items. While *Autoscore* and TSR were each designed for matching sentences, *lrd*’s sentence scoring matching provides additional functionality by including output for omitted and extra items from each participant’s response, allowing researchers to assess trends in participant responses such as commonly forgotten words. Finally, *lrd* includes several plotting and summary functions, allowing researchers to quickly assess trends in their scored output. Taken together, *lrd* provides a comprehensive set of tools for easily scoring lexical output from a variety of recall paradigms while also providing functions for easy data exploration.

**Summary and Conclusion**

Although recall tests are widely used in Psychology, few open access tools currently exist to quickly process the large amounts of lexical text data that these studies generate. The *lrd* package addresses this need by providing researchers with a means of automating multiple types of recall scoring as a means of saving time and minimize coding errors, while also being able to control for minor errors in participant responses. By using this package to replicate results from cued-recall, free-recall, and sentence-recall experiments, we show that *lrd* can accurately reproduce each type of data. We hope that *lrd* will both drastically reduce the amount of time spent coding lexical data while ensuring near-perfect accuracy and assist the reproducibility measures being adopted by the field by providing researchers with a standardized, open-source method for processing lexical output across psychological studies.

**Open Practices Statement**

The data for all experiments have been made available at https://osf.io/admyx/, and none of the experiments were preregistered.

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Table 1

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Maxwell and Buchanan (2020) | | Maxwell and Huff (in press) | |
| Scoring Criteria | % Sensitivity | % Specificity | % Sensitivity | % Specificity |
| *lrd* 0 | 99 | 94 | 99 | 93 |
| *lrd* 1 | 99 | 96 | 99 | 97 |
| *lrd* 2 | 97 | 96 | 97 | 98 |
| *lrd* 3 | 80 | 97 | 87 | 99 |
| *lrd* 4 | 47 | 98 | 62 | 99 |
| *lrd* 5 | 24 | 99 | 40 | 99 |

*Sensitivity and Specificity Results for Cued-Recall*

*Note.* Column labels indicate Levenshtein distance used at scoring. Values denote percentages.

Table 2

*Mean Recall Rates as a Function of Human Coded and lrd Scored Data Collapsed Across Item Type in Maxwell and Buchanan (2020).*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | *M* | HC | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd* 4 |
| Human Coded | 54.14 (3.47) | -- |  |  |  |  |  |
| *lrd* 0 | 50.72 (3.58) | 0.13 | -- |  |  |  |  |
| *lrd* 1 | 52.14 (3.57) | 0.07 | 0.05 | -- |  |  |  |
| *lrd* 2 | 53.37 (3.53) | 0.03 | 0.10 | 0.05 | -- |  |  |
| *lrd* 3 | 61.30 (2.91) | 0.29\* | 0.43\* | 0.37\* | 0.32\* | -- |  |
| *lrd* 4 | 77.42 (1.86) | 1.10\* | 1.24\* | 1.17\* | 1.12\* | 0.87\* | -- |
| *lrd* 5 | 88.48 (1.09) | 1.76\* | 1.88\* | 1.82\* | 1.77\* | 1.63\* | 0.96\* |

*Note.* Mean recall rates for each scoring condition. *95%* *CI*’s are in parentheses. HC = Human coded data. HC and *lrd* columns indicate Cohen’s *d* effect sizes for post-hoc comparisons, \* = *p* < .05.

Table 3

*Mean Recall rates as a Function of Human Coded and lrd Scored Data Collapsed Across Associative Direction Items in Maxwell and Huff (in press).*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | *M* | HC | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd* 4 |
| Human Coded | 43.96 (6.57) | -- |  |  |  |  |  |
| *lrd* 0 | 41.06 (6.59) | 0.21 | -- |  |  |  |  |
| *lrd* 1 | 43.11 (6.59) | 0.06 | 0.15 | -- |  |  |  |
| *lrd* 2 | 44.86 (6.58) | 0.06 | 0.28\* | 0.13 | -- |  |  |
| *lrd* 3 | 50.83 (6.42) | 0.52\* | 0.75\* | 0.59\* | 0.46\* | -- |  |
| *lrd* 4 | 64.84 (5.51) | 1.79\* | 2.08\* | 1.67\* | 1.74\* | 1.33\* | -- |
| *lrd 5* | 77.69 (4.21) | 3.15\* | 3.49\* | 3.15\* | 3.12\* | 2.81\* | 1.76\* |

*Note.* Mean recall rates for each scoring condition. *95% CI*s are in parentheses. HC = Human coded data. HC and *lrd* columns indicate Cohen’s *d* effect sizes for post-hoc comparisons, \* = *p* < .05.

Table 4

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Experiment | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd* 4 | *lrd* 5 |
| MB | .93 | .95 | .94 | .79 | .49 | .24 |
| MH | .94 | .97 | .96 | .85 | .59 | .36 |

*Inter-rater Reliability Statistics (Cohen’s κ) for Maxwell and Buchanan (2020) and Maxwell and Huff (in press)*

*Note.* MB = Maxwell and Buchanan, 2020; MH = Maxwell and Huff (in press). *lrd* columns indicate Levenshtein distance used at scoring*.* All values are Cohen’s *κ* between human scored data and data scored at each *lrd* cutoff.

Table 5

|  |  |  |  |
| --- | --- | --- | --- |
| List Type | Scoring Criteria | % Sensitivity | % Specificity |
| Ad-hoc | 0 | 96 | 94 |
|  | 1 | 96 | 95 |
|  | 2 | 94 | 95 |
|  | 3 | 95 | 96 |
|  | 4 | 91 | 96 |
|  | 5 | 90 | 96 |
|  |  |  |  |
| Categorical | 0 | 98 | 90 |
|  | 1  2  3  4 | 98  96  93  91 | 91  91  93  93 |
|  | 5 | 91 | 93 |
|  |  |  |  |
| Unrelated | 0 | 98 | 96 |
|  | 1 | 97 | 96 |
|  | 2 | 96 | 96 |
|  | 3 | 93 | 96 |
|  | 4 | 92 | 96 |
|  | 5 | 92 | 96 |

*Sensitivity and Specificity Results for Huff et al. (2018)*

*Note:* Analyses are split by list type. Scoring criteria indicates Levenshtein distance used when running prop\_correct\_multiple().

Table 6

*Mean Correct Free-recall as a Function of Human Coded and lrd Scored Data for each list type used in Huff et al. (2018)*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| List Type | Group | *M* | HC | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd 4* |
| Ad-hoc | Human Coded | 50.00 (2.78) | -- |  |  |  |  |  |
|  | *lrd* 0 | 49.29 (2.74) | 0.05 | -- |  |  |  |  |
|  | *lrd* 1 | 49.83 (2.73) | 0.01 | 0.03 | -- |  |  |  |
|  | *lrd* 2 | 50.69 (2.75) | 0.04 | 0.09 | 0.06 | -- |  |  |
|  | *lrd* 3 | 52.48 (3.16) | 0.15 | 0.19 | 0.16 | 0.11 | -- |  |
|  | *lrd* 4 | 53.10 (3.24) | 0.18 | 0.23 | 0.20 | 0.14 | 0.03 | -- |
|  | *lrd 5* | 53.15 (3.24) | 0.19 | 0.23 | 0.20 | 0.15 | 0.02 | < 0.01 |
|  |  |  |  |  |  |  |  |  |
| Categorical | Human Coded | 47.85 (2.50) | -- |  |  |  |  |  |
|  | *lrd* 0 | 44.15 (2.67) | 0.25\* | -- |  |  |  |  |
|  | *lrd* 1 | 44.83 (2.64) | 0.21 | 0.05 | -- |  |  |  |
|  | *lrd* 2 | 45.58 (2.70) | 0.14 | 0.10 | 0.05 | -- |  |  |
|  | *lrd* 3 | 48.54 (3.13) | 0.04 | 0.27\* | 0.23 | 0.18 | -- |  |
|  | *lrd* 4 | 49.56 (3.25) | 0.11 | 0.33\* | 0.29\* | 0.24 | 0.06 | -- |
|  | *lrd* 5 | 49.56 (3.25) | 0.11 | 0.33\* | 0.29\* | 0.24 | 0.06 | 0.00 |
|  |  |  |  |  |  |  |  |  |
| Unrelated | Human Coded | 37.99 (2.68) | -- |  |  |  |  |  |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | *lrd* 0 | 37.98 (2.76) | < 0.01 | -- |  |  |  |  |
|  | *lrd* 1 | 38.08 (2.77) | < 0.01 | < 0.01 | -- |  |  |  |
|  | *lrd* 2 | 38.94 (2.83) | 0.06 | 0.06 | 0.05 | -- |  |  |
|  | *lrd* 3 | 40.88 (3.37) | 0.17 | 0.17 | 0.16 | 0.11 | -- |  |
|  | *lrd* 4 | 41.17 (3.48) | 0.22 | 0.21 | 0.21 | 0.16 | 0.04 | -- |
|  | *lrd 5* | 41.17 (3.48) | 0.22 | 0.21 | 0.21 | 0.16 | 0.04 | 0.00 |
|  |  |  |  |  |  |  |  |  |

*Note.* Mean recall rates for each scoring condition. *95%* *CI*’s are in parentheses. HC = Human coded data. *lrd* columns and row labels indicate each of the tested cutoff criteria. HC and percentage columns indicate Cohen’s *d* effect sizes for post-hoc comparisons, \* = *p* < .05.

Table 7

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| List Type | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd* 4 | *lrd* 5 |
| Ad-hoc | .90 | .91 | .90 | .87 | .86 | .86 |
| Categorical | .89 | .89 | .88 | .86 | .85 | .85 |
| Unrelated | .93 | .94 | .92 | .88 | .86 | .86 |

*Inter-rater Reliability Statistics (Cohen’s κ) for Huff et al. (2018).*

*Note.* List Type corresponds to the three study lists conditions used in Huff et al. (2018). *lrd* columns indicate each of the tested cutoff criteria All values are Cohen’s *κ* between human scored data and data scored at each *lrd* cutoff.

Table 8

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Coder 1 | | Coder 2 | |
| Scoring Criteria | % Sensitivity | % Specificity | % Sensitivity | % Specificity |
| *lrd* 0 | 99 | 91 | 99 | 93 |
| *lrd* 1 | 97 | 96 | 97 | 98 |
| *lrd* 2 | 95 | 97 | 95 | 98 |
| *lrd* 3 | 87 | 99 | 87 | 99 |
| *lrd* 4 | 81 | 99 | 80 | 99 |
| *lrd* 5 | 78 | 99 | 78 | 99 |

*Sensitivity and Specificity Results for Geller et al. (2020)*

*Note.* Column labels indicate Levenshtein distance used at scoring. Values denote percentages. For completeness, we compare *lrd* sensitivity and specificity to both human coders from Geller et al. (2020).

Table 9

*Mean Correct Sentence-Recall as a Function of Human Coded and lrd Scored Data for each coder in Geller et al. (2020)*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Group | *M* | HC 1 | HC 2 | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd 4* |
| Human Coded 1 | 31.80 (2.88) | -- |  |  |  |  |  |  |
| Human Coded 2 | 31.30 (2.97) | 0.03 | -- |  |  |  |  |  |
| *lrd* 0 | 29.10 (2.81) | 0.18 | 0.15 | -- |  |  |  |  |
| *lrd* 1 | 32.90 (3.10) | 0.07 | 0.10 | 0.25 | -- |  |  |  |
| *lrd* 2 | 34.25 (3.18) | 0.16 | 0.19 | 0.34\* | 0.08 | -- |  |  |
| *lrd* 3 | 40.15 (3.55) | 0.51\* | 0.53\* | 0.66\* | 0.43\* | 0.34\* | -- |  |
| *lrd* 4 | 44.45 (3.79) | 0.74\* | 0.76\* | 0.91\* | 0.66\* | 0.58\* | 0.23 | -- |
| *lrd 5* | 46.45 (3.90) | 0.84\* | 0.86\* | 1.00\* | 0.75\* | 0.67\* | 0.33\* | 0.10 |

*Note.* Mean recall rates for each scoring condition. *95%* *CI*’s are in parentheses. HC = Human coded data. *lrd* columns and row labels indicate each of the tested cutoff criteria. HC and percentage columns indicate Cohen’s *d* effect sizes for post-hoc comparisons, \* = *p* < .05.

Table 10

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Coder | *lrd* 0 | *lrd* 1 | *lrd* 2 | *lrd* 3 | *lrd* 4 | *lrd* 5 |
| One | .93 | .92 | .90 | .81 | .72 | .69 |
| Two | .94 | .94 | .91 | .80 | .72 | .69 |

*Inter-rater Reliability Statistics (Cohen’s κ) for each human coder used in Geller et al. (2020)*

*Note.* *lrd* columns indicate Levenshtein distance used at scoring*.* All values are Cohen’s *κ* between human scored data and data scored at each *lrd* cutoff.



*Figure 1.* Illustration of the *lrd Shiny* application’s Instructions tab prior to uploading a dataset.





*Figure 2.* Illustration of the *lrd Shiny* application’s Cued-Recall tab prior to uploading a dataset and answer key (top panel) and the Scored Output panel after scoring (bottom panel). Data in this is example is scored using a Levenshtein distance of 1.



*Figure 3*. Illustration of the *lrd* *Shiny* application’s Arrange Data tab. This tab can be used to quickly convert wide format free-recall data into long format for scoring.



*Figure 4*. Illustration of the *lrd* *Shiny* application’s Free-Recall scoring tab after scoring. Data was scored using a Levenshtein distance of 1.



*Figure 5*. Illustration of the *lrd* *Shiny* application’s Sentence-Recall scoring tab after scoring. Data was scored using a Levenshtein distance of 1.

1. When copying code, please note that the arguments in quotes change color (usually green), as not all quote symbols are recognized by *R*. Simply delete them and retype the quotes if they do not copy correctly. > symbols indicate code has been executed in R. [↑](#footnote-ref-1)