A Toolkit for Analyzing Strategy Use in Phonemic Verbal Fluency Tasks

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The data used for the analysis described in this article were obtained from a dataset of 260 individuals, which was originally collected by Vance et al. as part of a longitudinal clinical trial that examined the effect of a computerized cognitive training protocol on cognitive functioning in middle-aged and older adults (40+) who had been diagnosed with HIV (Vance et al., 2017). The collection of that data was supported by funding from the Edward R. Roybal Center (P30 AG022838), a National Institutes of Health NIA K-award (PI: Fazeli:

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Abstract

The phonemic verbal fluency task is a common cognitive assessment of language and executive functioning which asks participants to list as many words as they can that begin with a given letter. Verbal fluency tasks are widely used to identify deficits in verbal fluency, which have been associated with disorders such as schizophrenia and dementia. Verbal fluency tasks are scored by the number of correct responses, however analysis of “clusters” of related words within a response list can give insights into the cognitive strategies used by participants. Unfortunately, manual word cluster analysis is time and labor intensive and inconsistent, since raters may cluster words differently depending on how they themselves have phonetically categorized the words. We present an automated pipeline for quantification of strategy use in the phonemic verbal fluency task, “LetterVF”. LetterVF is a python module (i.e., a script containing useful functions, which can be imported and used in other scripts) that uses a pronunciation dictionary to convert verbal fluency task data items into lists of phonemes, which can be analyzed to identify clusters of words that share similarities in any of several clustering categories. Additionally, LetterVF contains useful functions for identifying intrusions (words which do not follow the rules for the task), identifying perseverations (responses repeated within the same trial), counting the number of cluster switches in a list, and calculating the average size of clusters for a list. Analysis of data from 50 participants’ verbal fluency task responses indicated that analysis using LetterVF yields accuracy and consistency on par with manual analysis. Our hope is that this tool will allow researchers to get more out of their datasets, and explore new topics related to cognitive strategy use, such as how strategies change with age and differences in strategies between experimental groups.

54 **Key words:** verbal fluency, phonemic verbal fluency task, python, strategy

55 **Tools:** Python

Introduction

The verbal fluency task (VFT) has been one of the most common methods among researchers and clinicians for measuring language, verbal fluency, and executive functioning. A major reason for its wide-spread use is that it is an easy-to-administer test, which in a matter of minutes can give data related to a patient's ability to retrieve information from their memory (Bousfield & Sedgwick, 1944). During a fluency task, a participant is given a category and asked to list words from that category within a given time limit (usually one minute). There are two types of verbal fluency tasks: semantic verbal fluency tasks, in which participants are given a semantic category (e.g., animals), and phonemic verbal fluency, in which participants are given a letter with which all their responses must begin. Verbal fluency tasks are commonly used in the study of clinical disorders such as schizophrenia (Ojeda et al., 2010), Alzheimer's disease (Pakhomov & Hemmy, 2014), and Parkinson's disease (Koertz et al., 2012). Additionally, verbal fluency tasks are included in popular cognitive screening batteries such as the Montreal Cognitive Assessment (MoCA) (Nasreddine et al., 2005).

Typically, VFT responses are scored by the number of correct words given. Albeit, VFT data is richly structured, in that additional information can be collected from the same data set when researchers consider the order in which participants produce their responses and how they do so. By analyzing how consecutive responses relate to one another, it is possible for researchers to gain insight into the cognitive strategies that participants use during the task (Troyer, Moscovitch, & Winocur, 1997). For example, if a participant consecutively gives the responses "fit", "fight", and "foot", they have produced a cluster of related words which indicates that this participant may be using a strategy in which they change only a single vowel

sound. Understanding what cognitive strategies participants use and how they use them makes it possible for researchers to identify differences between individuals' performances.

Doing this type of word cluster analysis by hand, however, is time consuming and inconsistent. Word cluster analysis is time consuming because it requires a trained scorer to determine, item by item, the relationships between adjacent words in several categories. And word cluster analysis is inconsistent because many of those relationships are defined subjectively. For example, "Cot" and "caught" are pronounced in exactly the same way in some parts of the United States, but have distinct pronunciations in other places. Researchers may differ over whether or not they believe these words rhyme, and in any case it is sometimes impossible to consider all of the possible pronunciations and spellings of words. Some methods have been developed for automating word cluster analysis, however these efforts have primarily focused on automating the cluster scoring of semantic verbal fluency tasks (Shao et al., 2014; Zemla et al., 2020). Because there is not a common and fast way to complete cluster analyses on phonemic verbal fluency tasks, researchers are missing valuable information about the phonemic VFT. Here we present LetterVF.py, a python module (i.e., a python script which contains functions that can be imported into and used in other scripts) which contains functions for automating word cluster analysis of phonemic VFT data.

Method

Software Accessibility

LetterVF is free to use and modify according to the MIT license (Open Source Initiative, n.d.). LetterVF can be downloaded from <https://github.com/Visscher-Lab/LetterVF>, or by using the command `python3 -m pip install "LetterVF"`. LetterVF has functions that draw from the `numpy.py` and `xlsxwriter.py` python modules. If the user does not have either of these

packages installed and updated, installing LetterVF using pip will automatically install or update them. LetterVF was developed to be compatible with the formatting of CMUdict, which is an open-source North American English pronunciation dictionary created by researchers at Carnegie Mellon University (The Carnegie Mellon Speech Group, 1998). As such, if you will be using LetterVF for analyzing lists in North American English, we recommend using CMUdict with LetterVF, though any pronunciation dictionary will work so long as it is formatted as a plain text file where each line contains a single word followed by its phonemes, separated by spaces. CMUdict can be downloaded from their project’s website (<http://www.speech.cs.cmu.edu/cgi-bin/cmudict>), or by using the terminal command `python3 -m pip install cmudict`.

Formatting Datasets

LetterVF is designed to analyze a 3-column CSV file, where the first column contains a participant identification number, the second column contains a list identification number (for use cases where participants have multiple lists being analyzed at once), and the third column contains the responses given by the participant. The first row should act as a label for each column (e.g., the first cell of the first row might contain “Participant Identification Number” to make it clear for the user what kind of information is represented in each column. An example of what the data file should look like is in **Figure 1**. The participant identification numbers and list numbers can be formatted however the user prefers (i.e., can be codes containing letters as well), as long as the formatting is consistent.

participant_id	list_number	response
1	1	freckle
1	1	fry
1	1	fly
1	2	dolt
1	2	fair
1	2	fare
1	2	fall
2	1	flack
2	1	full
2	1	fetter
2	1	ferret
2	1	fend
2	1	faberge

Figure 1. Example of how a dataset .csv file should be formatted for use with lettVF.py.

Python Module

A pronunciation dictionary is used to look up and compare phonemes that are used for each word's pronunciation in order to analyze phonemic verbal fluency task data. Once a user has downloaded the LetterVF.py according to the instructions in the **Software Accessibility** section, and a properly formatted data file and pronunciation dictionary have been created, LetterVF.py can be used to analyze the data according to any one of several clustering algorithms that are included in LetterVF.py. **Figure 2** shows a basic overview of how LetterVF processes phonemic verbal fluency task data.

Figure 2. A basic overview of how LetterVF can analyze data from phonemic verbal fluency tasks.

Step #1: Importing LetterVF and setting up pronunciation dictionary

`import LetterVF as lvf` should be included at the top of a user's Python script in order to import all functions from LetterVF. The first step is to use `lvf.getPronDict()`. This function sets up the user's pronunciation dictionary for analysis. The first argument of `lvf.getPronDict()` is `character`, and it should be a string set to the target letter for the lists being analyzed (e.g., "f" for lists of words beginning with "f"). The second argument, `pron_dict_path`, should be a string which contains the pronunciation dictionary's file path. If the verbal fluency task being analyzed had restrictions on the types of words allowed (e.g., not allowing proper nouns), the user may want to utilize the third, optional parameter of `lvf.getPronDict()`, which is `removal_list_path`. This third parameter should be set to a string which contains the path for a file which lists any words to be removed from the pronunciation dictionary. This file can be either a csv or text file which contains on each line one word to be removed. The fourth and final argument to `lvf.getPronDict()`, `addendum_path`, is also optional, but useful for adding words to the pronunciation dictionary. This is useful in cases where the pronunciation dictionary being used does not contain entries for all valid responses given by participants. Setting `addendum_path` to a string containing the path to an addendum file will add any entries in that file to the pronunciation dictionary. An addendum file should be a csv file formatted so that each line contains a single word, followed by each of the phonemes of that word in separate cells. An example of what this addendum file should look like can be found in **Figure 3**.

In order to determine which phonemes to use for a given word, the user can sound out the word and assign phonemes based on their own judgement. CMUDict uses 2-letter ARPAbet symbols, a guide to which can be found on the project's website (The Carnegie Mellon Speech

Group, 1998). (ARPAbet symbols typically also include numbers after some symbols to indicate which syllables are stressed; however, these are unnecessary when creating files for use with LetterVF.) The current version of LetterVF does not take into account the stresses on different syllables, so it is not necessary to include any numbers for identifying stresses.

`lvf.getPronDict()` will return a list of strings, where each string is an item from the pronunciation dictionary which begins with the target letter. For words that have multiple pronunciations listed in the dictionary, the first pronunciation to appear in the dictionary is the one that will be used during analysis. An example of how to use `lvf.getPronDict()` can be found in **Listing 1**.

	A	B	C	D	E	F	G	H	I	J	K	L
1	fibber	F	IH	B	ER							
2	floozy	F	L	UW	Z	IY						
3	frugivore	F	R	UW	G	AH	V	OW	ER			
4	folivore	F	OW	L	OH	V	OW	ER				
5	finial	F	IH	N	IY	UH	L					
6	forementioned	F	OW	ER	M	IH	N	CH	Y	AH	N	D

Figure 3. Example of how .csv files should be formatted if the user wishes to add additional words to their preferred pronunciation dictionary.

Listing 1. Preparing a pronunciation dictionary using LetterVF

```
#import functions from letterVF
import LetterVF as lvf

# isolate all the entries that begin with target letter from a pronunciation
  dictionary
pron_dictF = lvf.getPronDict(character='f',
    pron_dict_path='cmudict-master/cmudict.dict',
    # remove remaining unwanted words
    removal_list_path='words_to_be_removed.csv',
    # create entries for missing valid responses
    addendum_path='words_to_be_added.csv')

# example output
> [..., 'facts f ae k t s', 'factual f ae k ch uw ah l', ...]
```

191 *Step #2: Identifying words missing from the pronunciation dictionary*

192 The second step is optional but recommended. `lvf.findIntrusions()` takes two
 193 arguments: `pron_dict` should be set to a pronunciation dictionary in the form of a list of strings
 194 (e.g., a list returned by `lvf.getPronDict()`), and `data_file_path` should be set to a string
 195 containing a data file path. This function returns a list of all of the intrusions that LetterVF could
 196 identify in the data file. Intrusions are any items in the data file that do not have a corresponding
 197 entry in the pronunciation dictionary. As such, valid responses may be marked as intrusions any
 198 time the pronunciation dictionary being used does not contain an entry for that response. In order
 199 to check whether your pronunciation dictionary contains entries for all valid responses in the data
 200 file, we recommend using `lvf.findIntrusions()` on the initial pronunciation dictionary to
 201 identify any valid responses that are incorrectly being identified as intrusions, then creating an
 202 addendum file and including it in the second iteration of the pronunciation dictionary. **Listing 2**
 203 shows how to find and show all intrusions found in a data file.

204

205 *Listing 2. Using `lvf.findIntrusions()` to identify intrusions in a dataset*

```

206 # find all intrusions across the "F" dataset
207 f_intrusions = lvf.findIntrusions(pron_dict=pron_dictF,
208     data_file_path='F_VFT_data.csv')
209
210 #print intrusions to the terminal window
211 for intrusion in f_intrusions:
212     print(intrusion)
213
214
215 #example output
216 > dolt
217   France
218   phony
219   ...
  
```

220
221

222

223 *Step #3: Identifying intrusions and perseverations and calculating clusters*

224 Once the user has a pronunciation dictionary that contains all and only the words which
 225 should be counted as valid, the third step involves using `lvf.findClusters()` to create an array
 226 which contains all of the data items and how they relate to the preceding item in each clustering
 227 category included. The first two parameters of `lvf.findClusters()` are `pron_dict` and
 228 `data_file_path`; these parameters behave exactly the same as they do in
 229 `lvf.findIntrusions()`. There are seven more optional parameters, and each one determines
 230 whether or not to include a specific clustering category in the clustering analysis. **Table 1** shows
 231 these parameters and explains what clustering category they represent. The clustering categories
 232 that are set to be included by default are `include_rhyme=True`, `first_letters=2`,
 233 `include_homophone=True`, and `lev_dist=1`. These categories were selected to be included by
 234 default because they are commonly used for scoring clusters (Troyer et al., 1997). In addition to
 235 scoring consecutive words according to each of the selected clustering algorithms, this function
 236 will automatically mark intrusions (i.e., invalid responses), mark perseverations (i.e., words that
 237 are repeated within a list), mark switches (i.e., where new clusters begin), and calculate the size
 238 of each cluster. Switches are considered to occur only when a word does not form a cluster with
 239 the previous word in any of the included clustering categories. For example, in **Listing 3**,
 240 `lvf.findClusters()` counts “freckle” and “fry” as part of the same because they share the
 241 same two first letters. However, “fly” is also considered a part of the same cluster despite the fact
 242 that it begins with “fl”, because it rhymes with “fry”. The first item of each list is not considered
 243 a switch. Perseverations can cluster with adjacent words, but intrusions cannot. Clusters of size 1
 244 are included, and intrusions are considered clusters of size 1.

245

246 *Listing 3.* Using `lvf.findClusters()` to identify words that group together according to the
 247 clustering algorithms included in analysis

```

248
249 # find clusters, switches, intrusions, perseverations, and cluster sizes for
250     each list
251 clust_listF = lvf.findClusters(prond_dict=pron_dictF,
252     data_file_path='F_VFT_data.csv')
253
254 #example output
255 > [['1','1','freckle',0,1,0,0,0,''],
256     ['1','1','fry',0,1,0,0,0,''],
257     ['1','1','fly',1,0,0,0,3],
258     ['1','2','dolt','intrusion','intrusion','intrusion','intrusion',1,1],
259     ['1','2','fair',0,0,0,0,1,''],
260     ['1','2','fare',1,1,1,1,0,2]
261     ...]
  
```

262
 263

264 **Table 1**

List of all optional parameters for the function `lvf.findClusters()`, as well as the default value of each parameter and a description of the clustering category that corresponds with each. The clustering categories included by default are `include_rhyme`, `first_letters`, `include_homophone`, and `lev_dist`.

Parameter	Default Value	Will cluster any 2 consecutive words which...
<code>include_rhyme</code>	True	share a common final syllable (i.e., syllabic rhyme)
<code>first_letters</code>	2	share the same first n letters, where n is the number assigned to the parameter
<code>include_homophone</code>	True	share the exact same pronunciation
<code>lev_dist</code>	1	can be transformed into one another by deleting, replacing, or inserting n phonemes, where n is the number assigned to the parameter
<code>include_beg_biphone</code>	False (not included in analysis by default)	share the same first 2 phonemes
<code>include_end_biphone</code>	False (not included in analysis by default)	share the same last 2 phonemes
<code>edit_dist</code>	None (not included in analysis by default)	can be transformed into one another by deleting or replacing, n phonemes, where n is the number assigned to the parameter

266 *Step #4: Calculating number of valid items, number of switches, and average cluster size*

267 Next the `lvf.clustSummary()` function can be used to create a second array which
268 contains the number of valid items in each list, the number of switches in each list, and the
269 average cluster size for each list. The only argument to `lvf.clustSummary()` is the array that
270 resulted from the use of `lvf.findClusters()`. Items are not counted as valid if they are either
271 intrusions or pereverations. Average cluster size is calculated by dividing the total number of
272 responses, including intrusions and perseverations, by the number of clusters. An example of
273 how to use `lvf.clustSummary()` can be seen in **Listing 4**.

274 *Step #5: Exporting to Excel file*

275 Finally, to export these tables as a single Excel file (as an .xlsx extension file), with
276 separate sheets for the word cluster analysis and summary, the user can use `lvf.sumExport()`.
277 This function has the parameters `clust_list`, which should be set to the array that resulted from
278 `lvf.findClusters()`, `clust_sum`, which should be set to the array resulting from
279 `lvf.clustSummary()`, and `output_path` which should be set to a string that names where the
280 xlsx file should be saved and what it should be saved as. Be sure to end the file name with the
281 .xlsx extension. **Listing 4** also shows how to use `lvf.sumExport`.

Listing 4. Using `lvf.clustSummary()` to calculate the number of valid responses, number of switches, and average cluster size for each list in a dataset, then using `lvf.sumExport()` to export analysis to a .xlsx file for ease of interpretation.

```
# find the number of valid items, number of switches, and average
cluster sizes for each list
clust_summaryF = lvf.clustSummary(clust_listF)

#example output
> [['1', '1', 3, 0, 3],
   ['1', '2', 3, 1, 2],
   ...]

#export analysis to a .xlsx file
lvf.sumExport(clust_listF, clust_sumF, 'F_HIV_VFT_output.xlsx')
```

Participants and Procedures

In order to validate this new method for performing cluster analysis on phonemic verbal fluency task data, response lists to the Controlled Oral Word Association Test (COWAT) were analyzed. These response lists come from a dataset of 260 individuals, which was originally collected by Vance et al. as part of a clinical trial that examined the effect of a computerized cognitive training protocol on cognitive functioning in people who were at least 40 years old and who had been diagnosed with HIV (Vance et al., 2017). The participants included in the 260-participant data set were recruited by placing flyers and other recruitment materials in a university HIV/AIDS clinic in an urban area in the Southern United States. The average age of the participants was 51.15 years old ($SD=6.76$, including ages ranging from 40 to 73). In this sample, 17.31% of the participants identified themselves as white and 64.23% identified as male (82.69% identified as non-white, 35.77% identified as female). The average number of years of education of the participants was 12.53 years ($SD=2.24$).

Cluster analysis was performed on COWAT response lists from 50 participants at baseline. Each participant completed three verbal fluency tasks, one for the letter “F”, one for “A”, and one for “S”.

First, the three lists from the 50 participants were scored manually. Items were considered a part of a cluster if the word and the preceding word either shared a common final syllable (i.e., syllabic rhyme), began with the same first two letters, the pronunciation of one word was different from the pronunciation of the other by only 1 phoneme, or the words were homophones. Names, proper nouns, and proper adjectives were considered intrusions, even if they began with the target letter. No intrusions were counted in clusters with other words. Words that did not cluster with other words, including intrusions, were considered to be clusters of size 1. Switches were defined between any two clusters, and the first response of each list was not counted as a switch.

The number of valid responses, number of switches, and average cluster size were calculated for each list. Perseverations were not counted as valid responses, but they were counted in clusters with adjacent words if they matched in any of the clustering categories. Average cluster size was calculated by dividing the number of switches by the number of responses (including intrusions and perseverations).

An equivalent to the hand-scored set of values was then completed using functions from LetterVF.py, according to the instructions and advice provided in the **Python Module** section above. For this analysis, the CMUDict pronunciation dictionary was used to get a list of phonemes for each word.

Percentage agreements and correlations were then calculated for the manual- and machine-found values for number of valid items, number of switches, and average cluster size across all “F”, “A”, and “S” response lists.

Results

Percentage agreements ranged from 76% to 100%. Correlation coefficients ranged from 0.955 to 1.00. Percentage agreements and correlation coefficients were highest across all letters for number of valid items, were slightly lower for the number of switches, and slightly lower again for the average cluster sizes. Percentage agreements and correlation coefficients were similar across “F,” “A,” and “S”; however, these values were slightly lower for “A.” All *p*-values for correlations were less than 0.001. **Table 2** shows the percentage agreements and correlation coefficients between the hand-calculated scores and machine-calculated scores associated with the number of valid items produced by participants, the number of switches between word clusters in each response list, and the average cluster size for each response list for each letter. **Figure 4** shows the plot of the hand-calculated scores versus the machine calculated scores for the number of valid items produced by participants, the number of switches between word clusters in each response list, and the average cluster size for each response list, again for each letter.

351 **Table 2**

Calculated percent agreements and Pearson's correlation coefficients for the number of valid items, number of switches, and average cluster sizes in manually-scored versus machine-scored trials.

	Number of Valid Items		Number of Switches		Average cluster size	
	% Agreement	Pearson's r	% Agreement	Pearson's r	% Agreement	Pearson's r
F	100	1.00	82	0.993	82	0.978
A	96	0.999	78	0.985	76	0.955
S	98	0.999	82	0.988	80	0.969

352

Figure 4. Scatterplots of hand-calculated scores versus machine-calculated scores for the number of valid items identified, number switches, and average cluster size of each list.

Discussion

The results suggest that using LetterVF.py to analyze phonemic verbal fluency task data produces results similar to results produced by human scorers using equivalent scoring criteria. There was a significant and high correlation between the values found by the human scorer and the values found using LetterVF.py across all 9 measures. Lower percentage differences in number of switches and average cluster size are likely due to the fact that these measures are more subjective than the count of valid responses. Differences in results between the two methods could be due to several factors, most likely related to human error and differences in the pronunciation listed in the dictionary and the pronunciation used by the human scorer.

This test of LetterVF.py was limited by the fact that only one human scorer was included in manual analysis, and by the fact that this experiment only tested the ability of LetterVF.py to analyze “F”, “A”, and “S”. LetterVF.py could be further validated in a similar study which uses multiple human scorers and compares the inter-rater reliability among human scorers with an inter-rater reliability between LetterVF.py and human scorers.

Our hope is that LetterVF.py may serve as an easy-to-use, flexible, and fast tool for researchers to use for cluster analyses of phonemic fluency data. By making VFT cluster analysis more accessible, we hope that researchers will have more opportunities to investigate understudied topics, such as differences in cognitive strategies between experimental groups, or how interventions may affect longitudinal changes in cognitive strategies within experimental groups. The clinical implications of LetterVF.py will be unknown until such studies are done, but it is our hope that analyses using LetterVF.py will be useful in cases where phonemic VFT data is already collected and used (e.g., in assessing people with Alzheimer’s disease or Parkinson’s disease).

In the future, we hope to update and expand LetterVF.py so that it remains relevant and useful for researchers. This may include improvements in the efficiency of the functions contained within LetterVF.py, the addition of clustering categories for users to pick from, and the addition of methods for identifying semantic relationships between data items (e.g. methods that can cluster “finch” and “falcon” based on the fact that they are both birds).

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