Parameter Estimation

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8/21/2019

A Brief Overview

This document supports a proposal to collect data in collaboration with the Psychological Science Accelerator. The purpose of this project is provide semantic priming data across many languages, inspired by the Semantic Priming Project (which is only in English; http://spp.montana.edu/; Hutchison et al., 2013). Big data sets are currency for those who do research in psycholinguistics, computational linguistics, natural language processing, and cognitive modeling. These data sets encourage controlled methodology and new scientific questions.

Cue words are defined as those shown first in a priming task, while target words are shown after the cue word. Semantic priming occurs when the target word is facilitated (i.e., responded to faster) in a related pair condition (DOCTOR-NURSE) versus an unrelated pair condition (TREE-NURSE). Therefore, in a priming task, one subject might see DOCTOR-NURSE, while another subject might see TREE-NURSE paired together. The two instances of NURSE will then be compared in an item analysis to see if the subjects who saw the related pairs responded to NURSE faster than the subjects who saw the unrelated pairs (however, some studies simply compare the average response latency of the unrelated condition to the related condition for a group level analysis).

One concern is how to estimate sample size necessary for any particular target word. The magic $N = 30$ has often been used, in an attempt to at least meet some perceived minimum criteria for the central limit theorem. Sample size planning has been promoted when there is a specific parameter goal, such as power to find X effect at specified alpha levels, but no good method has been suggested for knowing when the data around a single word has "settled". In this power / sample size analysis, we will focus on the lexical decision task in particular, wherein participants are simply asked if a concept presented to them is a word (NURSE) or nonsense word (LURSE). The dependent variable in this study is response latency, and we will use the data from the English Lexicon Project (http://elexicon.wustl.edu/; Balota et al., 2007) and the Semantic Priming Project (http://spp.montana.edu/; Hutchison et al., 2013) as the metric for our analysis.

Herein, we will also use concepts in accuracy in parameter estimates (AIPE) to think about how we can have the confidence intervals be "sufficiently narrow" (Kelley, 2007; Kelley, Darku, & Chattopadhyay, 2018; Maxwell, Kelley, & Rausch, 2008). Usually, AIPE power/sample size analysis focuses on the standardized mean difference, but here we instead want to know that the estimation of the response latency does not vary by some particular amount. Therefore, it seems that we actually want to focus on the standard error of the response latency, as this determines the width of the confidence interval.

Examining The English Lexicon Project (ELP)

The English Lexicon Project collected lexical decision (word or nonsense word) and naming (reading the word aloud) data for over 40,000 words. These data provide a good metric for the variability in base response latencies across words, which should allow for the estimation of the number of participants a study should use if the focus is on the standard error of response latencies.

Another issue to consider is that each participant likely has a somewhat arbitrary response latency factor. Usually, you would control for within-subject variance with a random intercept value in a multilevel type analysis, but another suggestion has been to standardize each participant's responses within a data collection session (Faust et al., 1999).

```
#read in the ELP data
ELPmaster <- read.csv("./ldt_raw/ELPDecisionData.csv")

#use the ave function to create a z-score of each participant
#they only did one session
ELPmaster$ZScore <- ave(ELPmaster$RT, #dependent variable
                        ELPmaster$Participant, #group variable
                        FUN = scale) #function, scale is z-scoring

#view the data
head(ELPmaster)
```

```
##   Trial Type Accuracy  RT      Stimulus  Participant     ZScore
## 1     1    1        0 707        bookie participant1  0.1030453
## 2     2    0        1 769     gandbrake participant1  0.4896557
## 3     3    1        1 526 philosophical participant1 -1.0256075
## 4     4    0        0 510      umbeaten participant1 -1.1253779
## 5     5    1        1 512     belonging participant1 -1.1129066
## 6     6    1        1 626      lowliest participant1 -0.4020424
```

Let's first remove all the inaccurate responses (i.e., they decided word/nonsense word incorrectly) and non-words because they do not represent the target words we wish to collect.

```
#exclude 0 accuracy for incorrect
#exclude 0 type, which is non-words
#subset is like filter in tidyverse
ELPcorrect <- subset(ELPmaster, #data frame
                     Accuracy > 0 & Type > 0) #logical rules to subset by

#droplevels simply excludes the non-word labels that we just dropped
ELPcorrect$Stimulus <- droplevels(ELPcorrect$Stimulus)
```

What is the average standard error for our standardized response latencies?

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
##summarize the dataframe to see what the average SE is
summary_stats <- ELPcorrect %>% #data frame
  select(ZScore, Stimulus) %>% #pick the columns
  group_by(Stimulus) %>% #put together the stimuli
  summarize(SES = sd(ZScore)/sqrt(length(ZScore)), samplesize = length(ZScore)) #create SE and the sample size for below

##give descriptives of the SEs
psych::describe(summary_stats$SES)
```

```
##    vars     n mean   sd median trimmed  mad  min  max range skew kurtosis
## X1    1 40455 0.16 0.1   0.14    0.15 0.06 0.01 3.33  3.32 4.71    65.45
##    se
## X1  0
```

From this output, we can see that the average and median SE hover around 0.14 to 0.16.

What is the average sample size after data loss due to incorrect answers? Note that there are several real words that only had one participant answer correctly, so they are included in the original sample sizes below, but not in the SE estimate. This explains why total n increases between the two code sections here.

```
##figure out the original sample sizes
original_SS <- ELPmaster %>% #data frame
  count(Stimulus) #count up the sample size

##add the original sample size to the data frame
summary_stats <- merge(summary_stats, original_SS, by = "Stimulus")

##original sample size average
psych::describe(summary_stats$n)
```

```
##    vars     n  mean   sd median trimmed mad min max range  skew kurtosis
## X1    1 40472 32.69 0.63     33   32.74   0  29  35     6 -0.91     1.45
##    se
## X1  0
```

```r
##reduced sample size
psych::describe(summary_stats$samplesize)
```

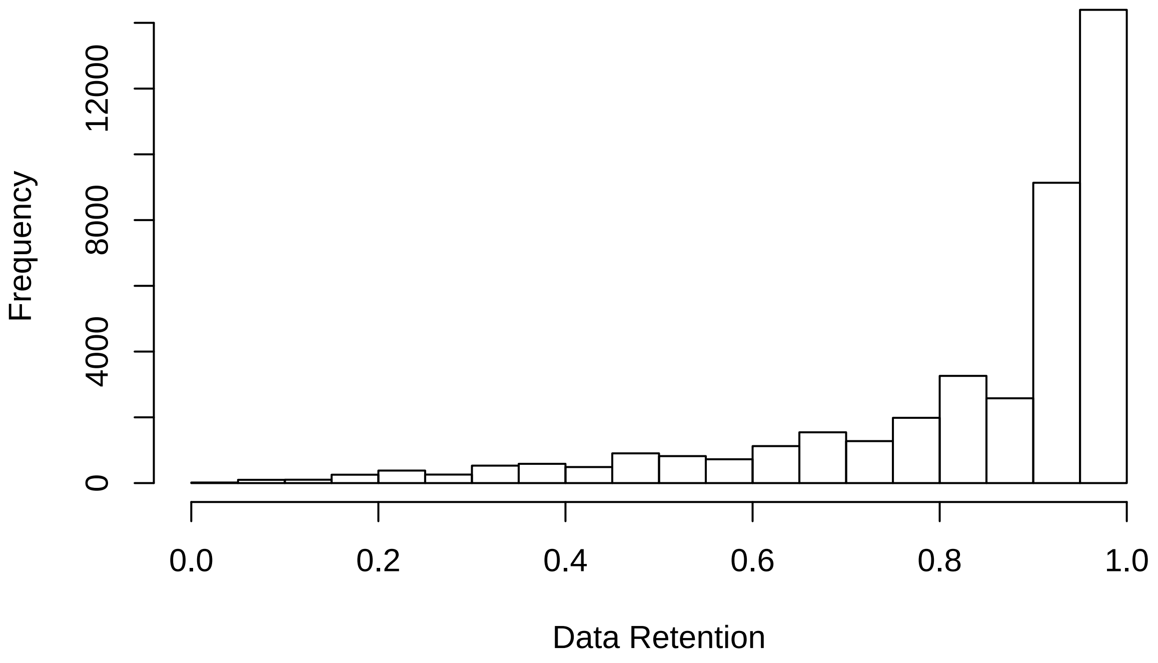
```
##    vars     n  mean   sd median trimmed  mad min max range  skew kurtosis
## X1    1 40472 27.41 6.43     30   28.64 2.97   1  35    34 -1.66      2.2
##      se
## X1 0.03
```

```r
##percent retained
psych::describe(summary_stats$samplesize/summary_stats$n)
```

```
##    vars     n mean  sd median trimmed  mad  min max range  skew kurtosis
## X1    1 40472 0.84 0.2   0.91    0.88 0.09 0.03   1  0.97 -1.68     2.25
##    se
## X1  0
```

We can see that on average, the ELP usually contained ~32 participants per word. The reduced sample size was about ~27 per word with an average retention rate of 84%. There are many weird words in the ELP (see the histogram of retention rates below, creating a skewed distribution), so the median retention rate might be a better estimation of data loss at ~ .91.

```r
##show the retention rates
hist(summary_stats$samplesize/summary_stats$n,
     xlab = "Data Retention",
     main = "")
```



Let's look at only the data above the magic $N = 30$ for the best estimate of what level of SE to use as our point at which we would consider the parameter accurate:

```r
##average SE for words with at least n = 30
summary_stats %>% #data frame
  filter(samplesize >=30) %>% #filter out lower sample sizes
  summarize(avgSES = mean(SES)) #create the mean
```

```
##      avgSES
## 1 0.1229559
```

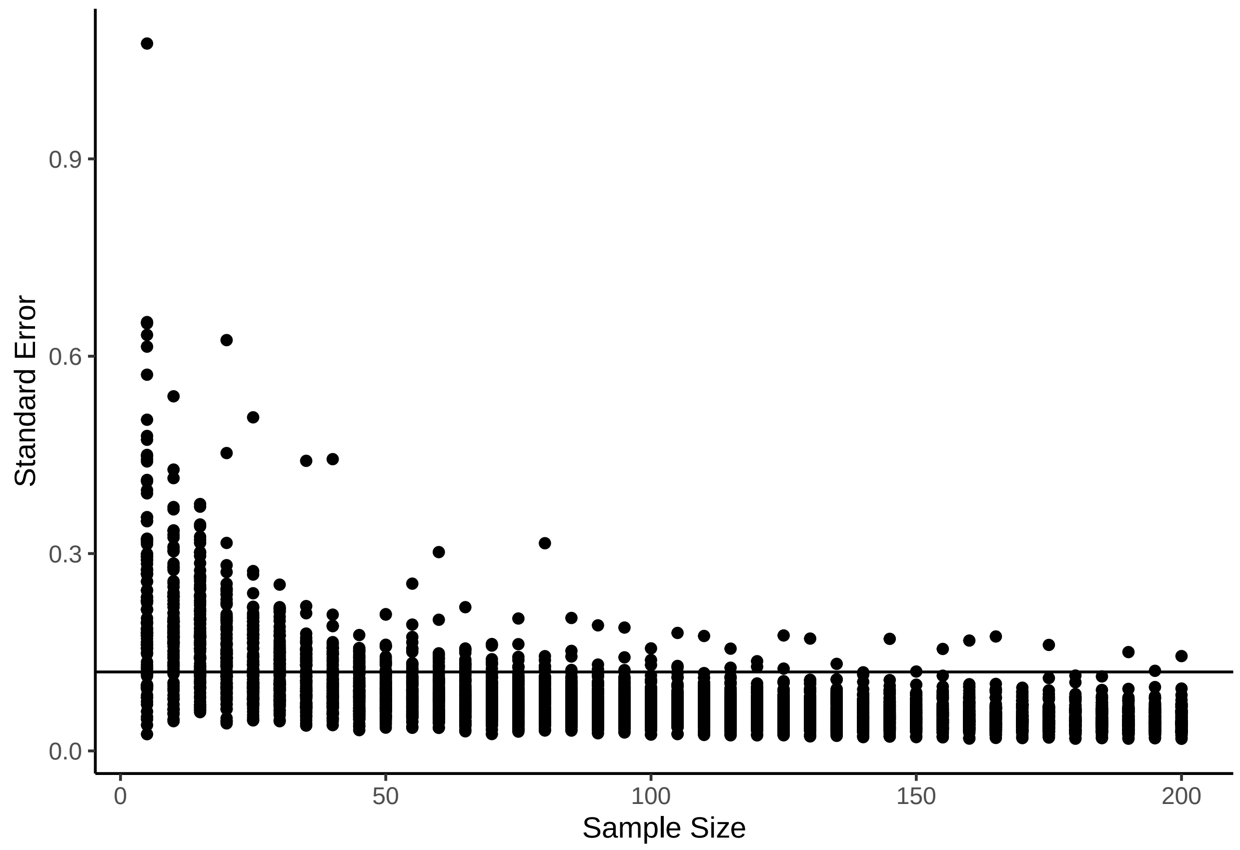
So, potentially, we could set the SE of the ZScore for an item to .12 as our metric of when to stop collecting data.

If I assume these data to be representative, what actual sample size might approximate SE = 0.12?

```r
##pick 100 random words with sample sizes above 30
targets <- summary_stats %>% #data frame
  filter(samplesize >=30) %>%  #filter out sample sizes
  select(Stimulus) %>% #select only stimuli
  sample_n(100) %>% #get 100
  pull(Stimulus) #return a vector
targets <- as.character(targets)

##this section creates a sequence of sample sizes to estimate at
#5, 10, 15, etc.
samplesize_values <- seq(5, 200, 5)
#create a blank table for us to save the values in
sim_table <- matrix(NA, nrow = length(samplesize_values), ncol = length(targets))
#create column names based on the current targets
colnames(sim_table) <- targets
#make it a data frame
sim_table <- as.data.frame(sim_table)
#add those sample size values
sim_table$sample_size <- samplesize_values

##loop over all the target words randomly selected
for (i in 1:length(targets)){

  ##loop over sample sizes
  for (q in 1:length(samplesize_values)){

    ##temporarily save a data frame of Zscores
    temp <- ELPcorrect %>% #data frame
      filter(Stimulus == targets[i])  %>% #pick rows that are the current target word
      sample_n(samplesize_values[q], replace = T) %>% #select sample size number of rows
      pull(ZScore)

    #put that in the table
    #find the sample size row and column we are working with
    #calculate SE sd/sqrt(n)
    sim_table[sim_table$sample_size == samplesize_values[q], targets[i]] <- sd(temp)/sqrt(length(temp))

    }

  }
```

Obviously, each run of this exercise will be different because it's randomly selected, but let's graph the data:

```
##load some libraries
library(ggplot2)
library(reshape)

##melt down the data into long format for ggplot2
sim_table_long <- melt(sim_table,
                      id = "sample_size")

##create a graph of the sample size by SE value
ggplot(sim_table_long, aes(sample_size, value)) +
  theme_classic() +
  xlab("Sample Size") +
  ylab("Standard Error") +
  geom_point() +
  geom_hline(yintercept = .12) #mark here .12 occurs
```



At what point is 80% of the data below .12?

```
##calculate the percent below .12
sim_table_long %>% #data frame
  group_by(sample_size) %>% #group by sample size
  summarize(Percent_Below = sum(value<=.12)) %>%  #is it less than .12
  print(n = nrow(.))
```

```
## # A tibble: 40 x 2
##    sample_size Percent_Below
##          <dbl>         <int>
##  1           5            21
##  2          10            18
##  3          15            27
##  4          20            36
##  5          25            52
##  6          30            53
##  7          35            62
##  8          40            72
##  9          45            73
## 10          50            85
## 11          55            84
## 12          60            89
## 13          65            86
## 14          70            93
## 15          75            92
## 16          80            93
## 17          85            95
## 18          90            97
## 19          95            96
## 20         100            97
## 21         105            97
## 22         110            99
## 23         115            98
## 24         120            98
## 25         125            98
## 26         130            99
## 27         135            99
## 28         140           100
## 29         145            99
## 30         150            99
## 31        155            99
## 32        160            99
## 33        165            99
## 34        170           100
## 35        175            99
## 36        180           100
## 37        185           100
## 38        190            99
## 39        195            99
## 40        200            99
```

Looks like the answer is ~ 50 give or take different variations of this random sampling. This estimate would be the minimum sample size per word.

Note: I took several runs of this simulation and the one below for the estimates listed - they may not perfectly match the current compiled version of this document, but are representative of the larger set of values I estimated.

Examining The Semantic Priming Project (SPP)

In the SPP, participants were given a lexical decision task with a priming cue word first. So, the task is the same as the ELP, however, they first saw a prime word, then made the lexical decision on the target word. The sample size of target words is 1661. We are using the already z-scored data for the response latencies. In the SPP, they provide an item level analysis of the average z-score priming (i.e., average z-score for the target word in the related minus unrelated condition). However, that data does not allow you to estimate when the priming estimate would be stable, as it's just one value for each prime-target pair. As mentioned in the full proposal, we would expect priming to be variable - it should be predicted by other psycholinguistic variables. Therefore, we should aim to create stable estimates for the z-scored response latencies in both the related and unrelated conditions. This aim would allow us to know that at least the response latencies are reliable, and variability in the final subtracted priming can be investigated for predictors.

```r
##read in the SPP data
SPPmaster <- read.csv("subjectdataLDT.csv")

##drop the nonwords and non accurate, this has already been z scored
SPPcorrect <- subset(SPPmaster, #data frame
                     target.ACC > 0 & lexicality == 1) #make sure it's accurate and lexicality = 1 are real words

##drop all unused stimuli and words
SPPcorrect$target <- droplevels(SPPcorrect$target)

#remove NAs from the Z target
SPPcorrect <- subset(SPPcorrect, #data frame
                     !is.na(Ztarget.RT)) #is not NA, only keep non-NA values
```

What is the average SE for our standardized response latencies for words in a priming task (rather than no priming lexical decision)?

```r
##summarize the dataframe to see what the average SE is
summary_stats <- SPPcorrect %>% #data frame
  select(Ztarget.RT, target) %>% #pick the columns
  group_by(target) %>% #put together the stimuli
  summarize(SES = sd(Ztarget.RT)/sqrt(length(Ztarget.RT)), samplesize = length(Ztarget.RT)) #create SE and the sample size for below

##give descriptives of the SEs
psych::describe(summary_stats$SES)
```

```
##    vars    n mean   sd median trimmed  mad  min  max range skew kurtosis
## X1    1 1661 0.06 0.01   0.06    0.06 0.01 0.04 0.16  0.12 2.19     11.4
##    se
## X1  0
```

In this study, they used a smaller subset of words (1661) as compared to the much larger set of English in ELP (40,000+). These words are likely to be similar to the words chosen for the study - because they are mostly somewhat frequent nouns, the variability in response latency is less than above. Here, we see it's about 0.06 for the standard error.

What is the average sample size after data loss due to incorrect answers?

```
##figure out the original sample sizes
original_SS <- SPPmaster %>% #data frame
  count(target) #count up the sample size

##add the original sample size to the data frame
summary_stats <- merge(summary_stats, original_SS, by = "target")

##original sample size average
psych::describe(summary_stats$n)
```

```
##    vars    n  mean   sd median trimmed  mad min max range  skew kurtosis
## X1    1 1661 255.2 1.36    255  255.26 1.48 251 258     7 -0.32    -0.15
##      se
## X1 0.03
```

```
##reduced sample size
psych::describe(summary_stats$samplesize)
```

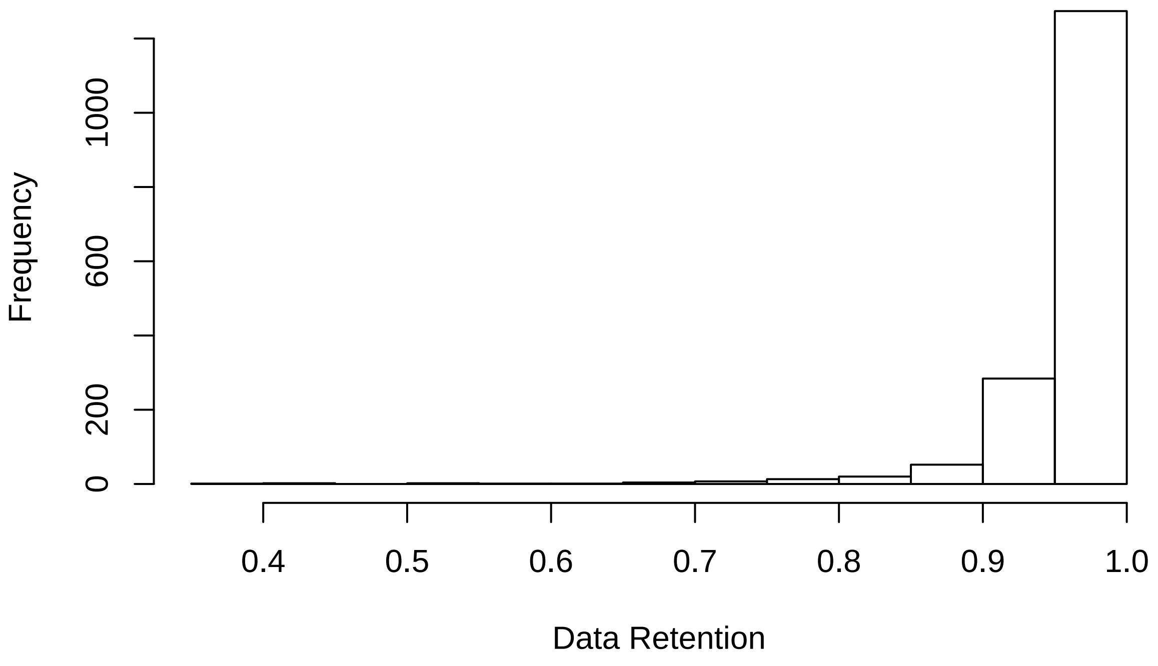
```
##    vars    n   mean    sd median trimmed  mad min max range  skew kurtosis
## X1    1 1661 244.23 12.64    247  246.51 4.45 101 257   156 -5.34    41.78
##      se
## X1 0.31
```

```
##percent retained
psych::describe(summary_stats$samplesize/summary_stats$n)
```

```
##    vars    n mean   sd median trimmed  mad  min max range  skew kurtosis
## X1    1 1661 0.96 0.05   0.97    0.97 0.02 0.39   1  0.61 -5.43    42.82
##    se
## X1  0
```

The original sample sizes are approximately ~256 participants, which is $n = 32$ for each of the eight possible conditions in the study. We are not going to use those conditions, so the entire data was collapsed for this analysis. The data retention is much better in this analysis at around 96%-97%, likely because the dataset includes fewer "weird" words.

```
##show the retention rates
hist(summary_stats$samplesize/summary_stats$n,
     xlab = "Data Retention",
     main = "")
```



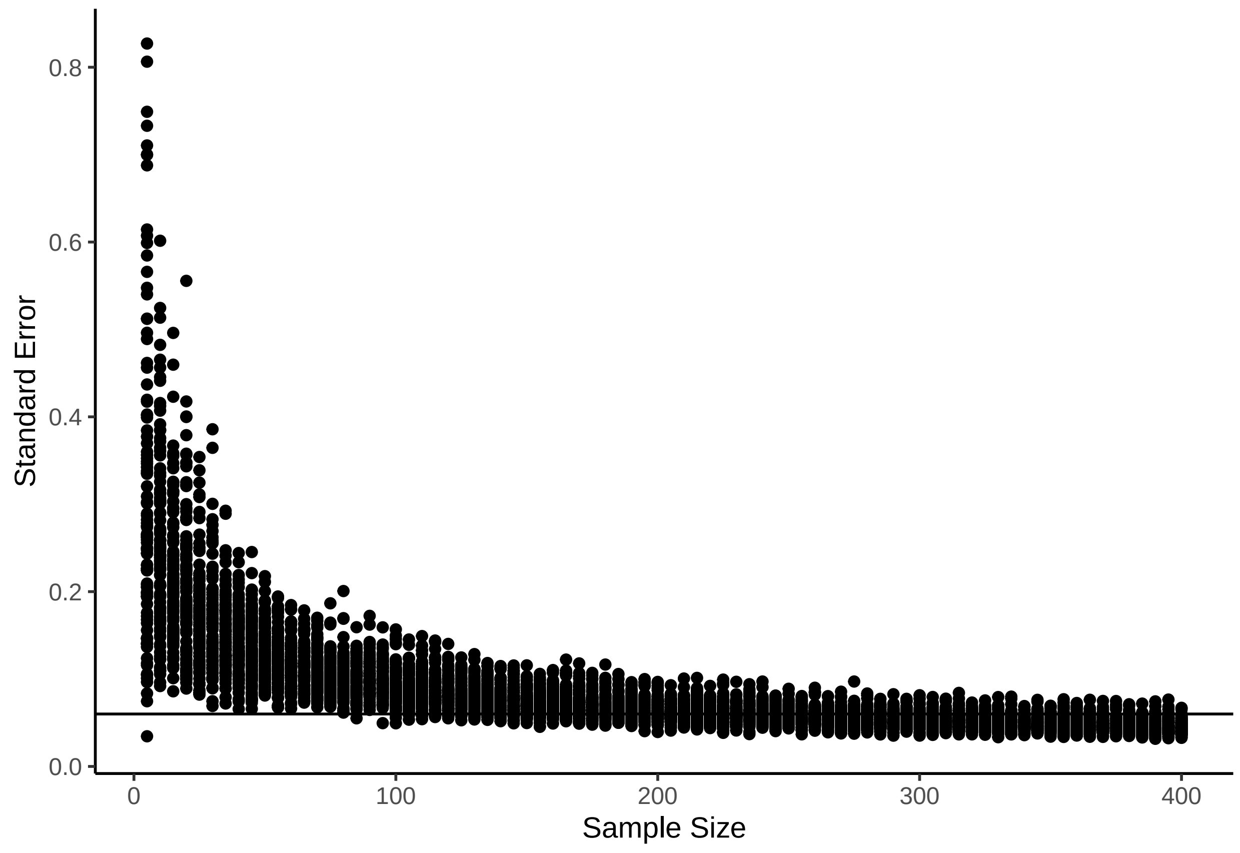
If I assume these data to be representative, what actual sample size would result in a SE = 0.06?

```
##pick 100 random words as all sample sizes are above 30
targets <- summary_stats %>% #data frame
  select(target) %>% #select only stimuli
  sample_n(100) %>% #get 100
  pull(target) #make it a vector
targets <- as.character(targets)
```

```r
##this section creates a sequence of sample sizes to estimate at
#5, 10, 15, etc.
samplesize_values <- seq(5, 400, 5)
#create a blank table for us to save the values in
sim_table <- matrix(NA, nrow = length(samplesize_values), ncol = length(targets))
#create column names based on the current targets
colnames(sim_table) <- targets
#make it a data frame
sim_table <- as.data.frame(sim_table)
#add those sample size values
sim_table$sample_size <- samplesize_values

##loop over all the target words randomly selected
for (i in 1:length(targets)){

  ##loop over sample sizes
  for (q in 1:length(samplesize_values)){

    ##temporarily save a data frame of Zscores
    temp <- SPPcorrect %>% #data frame
      filter(target == targets[i])  %>% #pick rows that are the current target word
      sample_n(samplesize_values[q], replace = T) %>% #select sample size number of rows
      pull(Ztarget.RT)

    #put that in the table
    #find the sample size row and column we are working with
    #calculate SE sd/sqrt(n)
    sim_table[sim_table$sample_size == samplesize_values[q], targets[i]] <- sd(temp)/sqrt(length(temp))

    }

  }
```

A graph of this data:

```r
##melt down the data into long format for ggplot2
sim_table_long2 <- melt(sim_table,
                      id = "sample_size")

##create a graph of the sample size by SE value
ggplot(sim_table_long2, aes(sample_size, value)) +
  theme_classic() +
  xlab("Sample Size") +
  ylab("Standard Error") +
  geom_point() +
  geom_hline(yintercept = .06) #mark here .06 occurs
```



At what point is 80% of the data below .06?

```r
##calculate the percent below .06
sim_table_long2 %>% #data frame
  group_by(sample_size) %>% #group by sample size
  summarize(Percent_Below = sum(value<=.06)) %>%  #is it less than .06
  print(n = nrow(.))
```

```
## # A tibble: 80 x 2
##    sample_size Percent_Below
##          <dbl>         <int>
##  1           5             1
##  2          10             0
##  3          15             0
##  4          20             0
##  5          25             0
##  6          30             0
##  7          35             0
##  8          40             0
##  9          45             0
## 10          50             0
## 11          55             0
## 12          60             0
## 13          65             0
## 14          70             0
## 15          75             0
## 16          80             0
## 17          85             1
## 18          90             0
## 19          95             1
## 20         100             3
## 21         105             2
## 22         110             5
## 23         115             3
## 24         120             5
## 25         125             6
## 26         130             7
## 27         135             6
## 28         140             6
## 29         145            13
## 30         150            11
## 31         155            15
## 32         160             7
## 33         165            10
## 34         170            17
## 35         175            23
## 36         180            25
## 37         185            27
## 38         190            24
## 39         195            29
## 40         200            35
## 41         205            46
## 42         210            33
## 43         215            43
## 44         220            43
## 45         225            50
## 46         230            53
## 47         235            51
## 48         240            56
## 49         245            58
## 50         250            63
## 51         255            61
## 52         260            66
## 53         265            63
## 54         270            72
## 55         275            71
## 56         280            76
## 57         285            70
## 58         290            80
## 59         295            75
## 60         300            82
## 61         305            76
## 62         310            85
## 63         315            83
## 64         320            85
## 65         325            86
## 66         330            89
## 67         335            82
## 68         340            92
## 69         345            93
## 70         350            91
## 71         355            91
## 72         360            94
## 73         365            92
## 74         370            94
## 75         375            96
## 76         380            92
## 77         385            97
## 78         390            96
## 79         395            94
## 80         400            97
```

Here the required number of participants per word would be ~320 participants.

Summary and Suggestions

In each session, participants would judge multiple words. In the SPP, each person judged 800 words per session, while in the ELP included 1,200 words per session. This facet should be considering for timing of the experiment, especially fatigue.

Estimation formulas:

```r
##how many words per session
##go a little less since it's a boring task
words_per_session <- 600

##words are assigned 25% related, 25% unrelated, 50% nonwords
##this keeps relatedness to 50/50 for real words, which is what SPP did
##also keeps yes/no lexical decision to 50/50
##also remember you will rate the prime word but it doesn't count
usable_words_per_session <- words_per_session * .50 / 2

##each word has to be collected in both unrelated and related conditions
conditions <- 2

##estimated participants from above
lower_est <- 50
```

```
upper_est <- 320

##data loss conservative estimate from ELP, since online studies may have more
data_loss <- .9

##target word goal
#number of targets we wish to achieve
number_of_targets <- 1000

##total estimated participants
((1/data_loss) * #incorporate data loss
  lower_est * #number of participants needed for each word
  conditions * #number of conditions each word has to appear in
  number_of_targets) / #number of total words
  usable_words_per_session
```

```
## [1] 740.7407
```

```
##total estimated participants
((1/data_loss) * #incorporate data loss
  upper_est * #number of participants needed for each word
  conditions * #number of conditions each word has to appear in
  number_of_targets) / #number of total words
  usable_words_per_session
```

```
## [1] 4740.741
```

The formula works as follows: We will incorporate expected data loss by multiplying by a percent increase one would need to accomodate that loss. This score is then multiplied by the estimates of persons per word for accuracy in parameter estimation. Each word must be seen in the related and unrelated condition, and these are not repeated within-subjects, therefore, we will double the estimate for the two conditions. This number is then multiplied by a desired number of target words, and 1000 words is the goal for this study. That value is divided by the useable number of words per session from a participant. In priming studies, you need to control for relatedness proprotions by keeping a balance of unrelated and related target words, as well as the balance of yes/no answers for the lexical decision task. Therefore, they are allocated at 25% for each of the real words (related/unrelated) and 50% for non-words. Therefore, each participant only provides 50% useable words, which is then further divided by two to only capture target words (i.e., ignoring prime words).

The estimates indicate that between 741 and 4741 participants would be necessary to gather 1000 real word targets in related and unrelated conditions for the study. This value would be the target sample size for each of the languages in the study.

Stopping Procedure

Because the variability of the sample size is quite large, we will employ a stopping procedure to ensure participant time and effort is maximized, and data collection is minimized. The minimum sample size will be 50 participants per concept or 741 total participants. After 50 participants, each concept will be examined for standard error, and data collection for that concept will be stopped when the standard error reaches an average of the two metrics found in this exploration (0.06, 0.12) or 0.09. This process will be automated online and checked in a daily subroutine, and words that meet the stopping rule criteria will be removed from further data collection. From the current simulations, this approximates to 100 to 150 participants per word, and 1482 to 2223 participants per language total. The maximum number of participants per word will be $n = 320$ from estimations above.

```
##calculate the percent below .09
sim_table_long %>% #data frame
  group_by(sample_size) %>% #group by sample size
  summarize(Percent_Below = sum(value<=.09)) %>%  #is it less than .09
  print(n = nrow(.))
```

```
## # A tibble: 40 x 2
##    sample_size Percent_Below
##          <dbl>         <int>
##  1           5            10
##  2          10            11
##  3          15            11
##  4          20            16
##  5          25            25
##  6          30            25
##  7          35            38
##  8          40            45
##  9          45            48
## 10          50            54
## 11          55            58
## 12          60            66
## 13          65            68
## 14          70            70
## 15          75            72
## 16          80            73
## 17          85            80
## 18          90            79
## 19          95            83
## 20         100            85
## 21         105            90
## 22         110            88
## 23         115            91
## 24         120            90
## 25         125            93
## 26         130            91
## 27         135            95
## 28         140            96
## 29         145            95
## 30         150            98
## 31         155            96
## 32         160            95
## 33         165            95
## 34         170            98
## 35         175            97
## 36         180            98
## 37         185            98
## 38         190            98
## 39         195            98
## 40         200            98
```

```
##calculate the percent below .09
sim_table_long2 %>% #data frame
  group_by(sample_size) %>% #group by sample size
  summarize(Percent_Below = sum(value<=.09)) %>%  #is it less than .09
  print(n = nrow(.))
```

```
## # A tibble: 80 x 2
##    sample_size Percent_Below
##          <dbl>         <int>
##  1           5             3
##  2          10             0
##  3          15             1
##  4          20             1
##  5          25             4
##  6          30             4
##  7          35             4
##  8          40             5
##  9          45             9
## 10          50             8
## 11          55            10
## 12          60            19
## 13          65            17
## 14          70            23
## 15          75            32
## 16          80            31
## 17          85            30
## 18          90            39
## 19          95            37
## 20         100            61
## 21         105            60
## 22         110            56
## 23         115            60
## 24         120            73
## 25         125            78
## 26         130            78
## 27         135            80
## 28         140            87
## 29         145            83
## 30         150            87
## 31         155            90
## 32         160            90
## 33         165            92
## 34         170            90
## 35         175            93
## 36         180            95
## 37         185            96
## 38         190            97
## 39         195            95
## 40         200            97
## 41         205            99
## 42         210            98
## 43         215            99
## 44         220            99
## 45         225            97
## 46         230            99
## 47         235            99
## 48         240            98
## 49         245           100
## 50         250           100
## 51         255           100
## 52         260            99
## 53         265           100
## 54         270           100
## 55         275            99
## 56         280           100
## 57         285           100
## 58         290           100
## 59         295           100
## 60         300           100
## 61         305           100
## 62         310           100
## 63         315           100
## 64         320           100
## 65         325           100
## 66         330           100
## 67         335           100
## 68         340           100
## 69         345           100
## 70         350           100
## 71         355           100
## 72         360           100
## 73         365           100
## 74         370           100
## 75         375           100
## 76         380           100
## 77         385           100
## 78         390           100
## 79         395           100
## 80         400           100
```

```r
##how many words per session
##go a little less since it's a boring task
words_per_session <- 600

##words are assigned 25% related, 25% unrelated, 50% nonwords
##this keeps relatedness to 50/50 for real words, which is what SPP did
##also keeps yes/no lexical decision to 50/50
##also remember you will rate the prime word but it doesn't count
usable_words_per_session <- words_per_session * .50 / 2

##each word has to collected in both unrelated and related conditions
conditions <- 2

##estimated participants from above
lower_est <- 100
upper_est <- 150

##data loss conservative estimate from ELP, since online studies may have more
data_loss <- .9

##target word goal
#number of targets we wish to achieve
number_of_targets <- 1000

##total estimated participants
((1/data_loss) * #incorporate data loss
  lower_est * #number of participants needed for each word
  conditions * #number of conditions each word has to appear in
  number_of_targets) / #number of total words
  usable_words_per_session
```

```
## [1] 1481.481
```

```r
##total estimated participants
((1/data_loss) * #incorporate data loss
  upper_est * #number of participants needed for each word
  conditions * #number of conditions each word has to appear in
  number_of_targets) / #number of total words
  usable_words_per_session
```

```
## [1] 2222.222
```