GazeR: A Package for Processing Gaze Position and Pupil Size Data

Jason Geller[1], Matthew B. Winn[2], Tristian Mahr[3], & Daniel Mirman[4]
[1] University of Iowa
[2] University of Minnesota
[3] University of Wisconsin-Madison

[4] University of Alabama at Birmingham

Author note

1) Department of Psychological & Brain Sciences
The University of Iowa
Iowa City, IA 52242

2) Department of Speech-Language-Hearing Sciences
164 Pillsbury Dr. SE

Minneapolis, MN 555455

3) Waisman Center
1500 Highland Ave
Madison, WI 53705

4) Department of Psychology

1300 University Blvd

Birmingham, AL 35205

Correspondence concerning this article should be addressed to Jason Geller, Department of Psychological & Brain Sciences, University of Iowa. E-mail: jason-geller@uiowa.edu

Abstract

Eye-tracking is widely used throughout the scientific community, from vision science and psycholinguistics, to marketing and human-computer interaction. Surprisingly, there is little consistency and transparency in preprocessing steps, making replicability difficult. To increase replicability and transparency, a package in R (a free and widely used statistical programming environment) called gazeR was created to read in and preprocess two types of data from the SR EyeLink eye tracker: gaze position and pupil size. For gaze position data, gazeR has functions for: reading in raw eye-tracking data, formatting it for analysis, converting from gaze coordinates to areas of interest, and binning and aggregating data. For data from pupillometry studies, the gazeR package has functions for: reading in and merging multiple raw pupil data files, removing observations with too much missing data, eliminating artifacts, blink identification and interpolation, subtractive baseline correction, and binning and aggregating data. The package is open-source and freely available for download and installation: https://github.com/dmirman/gazer. We provide step-by-step analyses of data from two tasks exemplifying the package's capabilities.

Keywords: eye-tracking, open science, pupillometry, visual world paradigm,R,

Word count: 8,938

GazeR: A package for processing gaze position and pupil size data

Introduction

Recent advances in eye-tracking technology make it a highly powerful and relatively inexpensive tool to gather fine-grained measures of the temporal dynamics of cognitive processing. Because of this, a growing number of fields from vision science and psycholinguistics, to marketing and human-computer interaction, have adopted this methodology. Despite its growing presence, there is a lot of variability in how eye-tracking data are processed. While there are many open-source tools for processing eye-tracking data, written in a variety of programming languages (e.g., R, Python, or MATLAB), they implement different processing conventions, some of which could be sub-optimal. In addition, some of these tools are not accessible to all users because they require proprietary or costly software (e.g., MATLAB). In the current climate where replicability and transparency are becoming more common, there is a need for a cross-platform, fully free implementation of standard practices in eye-tracking data processing. To this end, we have created the gazeR package in R (R Core Team 2018), which is a free, open-source statistical programming language, to aid researchers in analyzing eye-tracking data that comes from visual world paradigms and pupil dilation experiments. The package is implemented in R because it is the dominant environment for statistical analysis and visualization of eye-tracking data. Therefore, the gazeR package facilitates end-to-end analysis of eye-tracking data within a single programming environment – from reading in raw data files to statistical analysis and generating figures. The initial release version of gazeR is designed for use with the SR EyeLink eye-tracker, and extensions to other eye-trackers should be fairly straightforward.

In this paper, we provide a step-by-step walk through of how to use the gazeR package to analyze data from experiments in which the primary outcome measure is gaze position or pupil size. There are several conceptual or theoretical discussions on best practices when analyzing pupil and gaze data available elsewhere (see Mathôt et al., 2018; Winn, Wendt, Koelewijn, and Kuchinsky, 2018; Salverda & Tanenhaus, 2018). The main aim of the present paper is to illustrate and explain how to analyze gaze and pupil data in a more standardized way using gazeR, such that it may be used by researchers to analyze their own data. While there exist various packages and online resources to get started with eye-tracking, such materials are limited to the analysis of a single subject and do not represent what researchers actually want to do with their data. A secondary aim is to facilitate reproducible and transparent preprocessing of these types of data, using conventional practices in eye-tracking data processing, and smoothing the transition from data preprocessing to data analysis and visualization. In the remainder of this report, we provide a step-by-step walk through of the installation and core functionality of the gazeR package.

Package Installation and Setup

Raw Data

At the time of this writing, the gazeR package supports processing of data collected using an SR Research EyeLink eye tracker and exported using SR Research Data Viewer software, which generates a comma-separated text file consisting of either the full set of individual samples (“Sample Report”) or parsed fixations (“Fixation Report”).

Package Installation

The gazeR package can be installed along with helper packages using the remotes package:

```
library(remotes)
remotes::install_github("dmirman/gazer") #installs package from github
```

Once this has been completed, gazeR can be installed by typing the following into the command line:

```
library(gazer)
library(tidyverse)
library(zoo)
library(knitr)
```

Once the gazeR package has been installed you are now ready to start preprocessing data!

Preprocessing Gaze Position Data from the Visual World Paradigm

In a typical instantiation of the Visual World Paradigm (VWP), participants hear spoken instructions to manipulate or select one of several images on a computer screen or objects in the real world (Cooper, 1974; Tanenhaus, Spivey-Knowlton, Eberhard, & Sedivy, 1995). Decades of research have shown that the time course of fixation proportions – that is, the probability of fixating a particular object at a particular time – reflect the activation of that object's mental representation. Figure 1 illustrates a typical VWP task. In this example (from Mirman & Graziano, 2012), the study examined semantic competition: the display contained a critical distractor that was related to the target either thematically (associates; e.g., *dog-leash*; shown in the left panel of Figure 1) or taxonomically (e.g., *apple-pear*). On each trial, the display contained a target object image, a semantic competitor (taxonomically or thematically related), and two unrelated distractors. The outcome measure was the probability of looks (fixation proportion) to a particular object at each point in time (example data shown in the right panel of Figure 1).

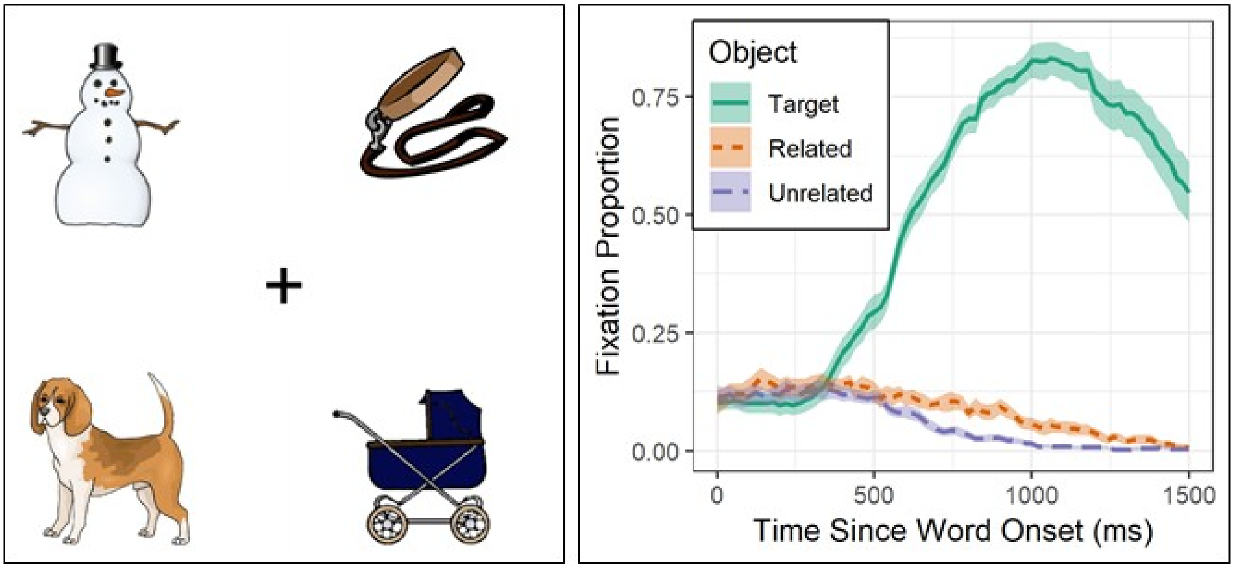


Figure 1. Left: Example display from a VWP experiment. The target is dog, the critical semantic competitor is leash (thematically related to the target), and snowman and carriage are unrelated distractors. Right: Example data showing the time course of target word recognition (soild line) and semantic competition: the semantically related competitor (dotted line) was fixated more than the unrelated distractors (dashed line).

Gaze preprocessing requires three main steps:

(1) Reading in the data

(2) Assigning areas of interest

(3) Binning fixations

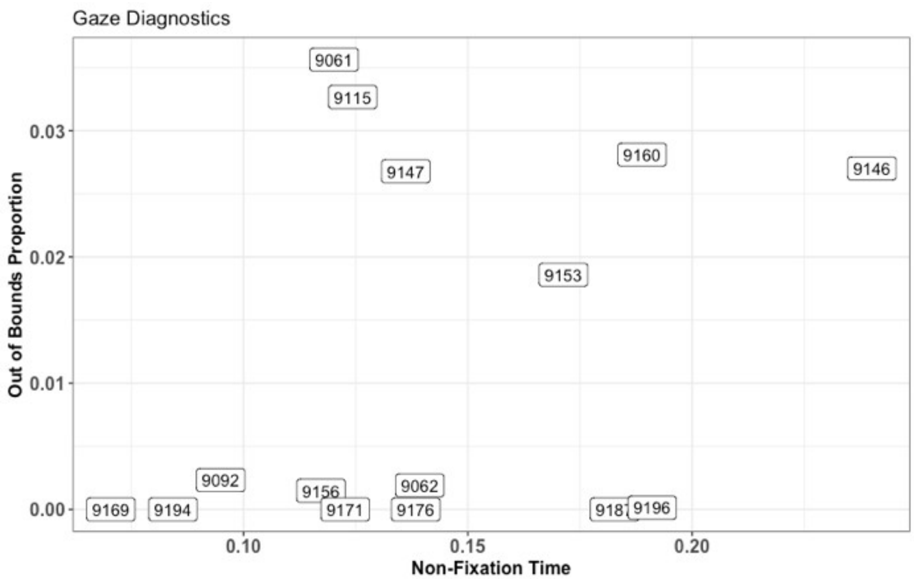
Reading in Gaze Data

Gaze data need to be read from the Fixation Report file generated by the EyeLink Data Viewer application. The `read_fixation_report`() function will read in the fixation report file. By default, this function will also generate two plots: (1) a scatter plot showing participant-level proportion of time spent not in fixations and proportion of time spend with gaze outside the bounds of the screen (Figure 2, top), which can be used as calibration diagnostics; (2) scatter plots for each participant showing fixation positions and durations, along with a red rectangle that shows the screen edges (Figure 2, bottom), which can be used to check for any systematic calibration issues. A pdf file is generated for all the participants and is saved in your directory. The non-fixation and out-of-bounds proportions can also be calculated using `get_gaze_diagnostics`() function.

Example[1]

```
gaze_path <- system.file("extdata", "FixData_v1_N15.xls", package =
"gazer")
gaze <- read_fixation_report(gaze_path, plot_fix_scatter = TRUE)
```

[1] The first line of code defines the path to the fixation report file included with the package. Because package installations differ across platforms and users, this line is necessary to define the user-specific path to the included data file. More generally, when a user wants to analyze their own data set, the `gaze_path` variable will need to be the path to that data file.


Gaze Diagnostics
Out of Bounds Proportion
Non-Fixation Time
0.00
0.01
0.02
0.03
0.10
0.15
0.20
9061
9115
9147
9160
9146
9153
9092
9156
9062
9169
9194
9171
9176
9196

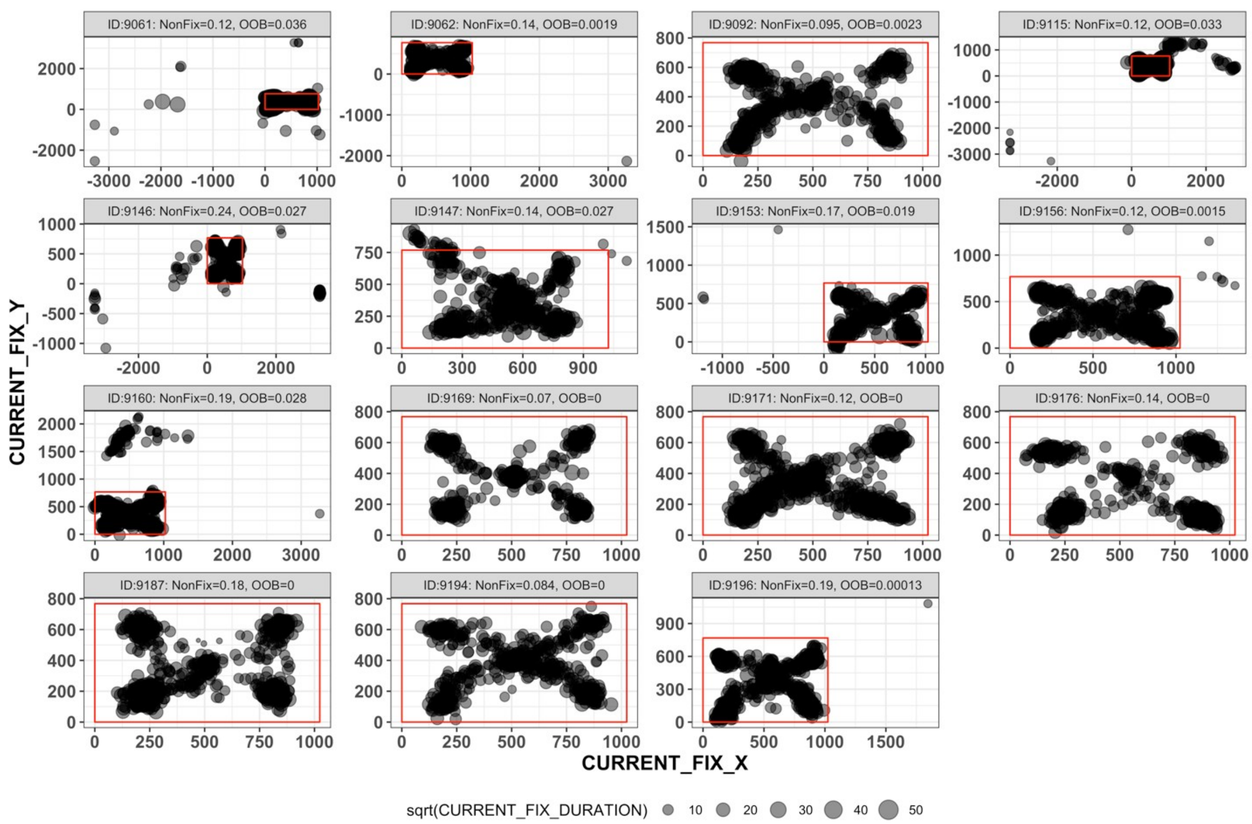

ID:9061: NonFix=0.12, OOB=0.036
ID:9062: NonFix=0.14, OOB=0.0019
ID:9092: NonFix=0.095, OOB=0.0023
ID:9115: NonFix=0.12, OOB=0.033
ID:9146: NonFix=0.24, OOB=0.027
ID:9147: NonFix=0.14, OOB=0.027
ID:9153: NonFix=0.17, OOB=0.019
ID:9156: NonFix=0.12, OOB=0.0015
ID:9160: NonFix=0.19, OOB=0.028
ID:9169: NonFix=0.07, OOB=0
ID:9171: NonFix=0.12, OOB=0
ID:9176: NonFix=0.14, OOB=0
ID:9187: NonFix=0.18, OOB=0
ID:9194: NonFix=0.084, OOB=0
ID:9196: NonFix=0.19, OOB=0.00013
CURRENT_FIX_Y
CURRENT_FIX_X
sqrt(CURRENT_FIX_DURATION) 10 20 30 40 50

Figure 2. Plots generated when reading in fixation data. Top: gaze diagnostics. Horizontal axis is non-fixation time, vertical axis is proportion of looking time outside of screen boundaries. High values on these dimensions suggest possibly poor calibration or track quality. Bottom: scatterplots of fixation locations. Red rectangle indicates screen boundaries, circle size indicates fixation duration (square-root scaled so that perceptual effect of circle size better matches fixation duration). Most fixations should be in the corners (where the objects are) and the center cross. Systematic deviations or looks outside the suggest poor calibration.

For this example data set, the fixation report contains eye-tracking variables that are created by EyeLink (fixation duration, fixation position, pupil size, etc.) and experiment-specific values (positions of different objects, trial condition, participant accuracy and response time) that are provided by the experiment software (in this case, E-Prime).

Table 1. Visual World Data Description and Structure

Variable	Class	Contents	Source
Subject	integer	Label of the data file	SR Eyelink
CURRENT_FIX_PUPIL	double	Pupil size of the current fixation	SR Eyelink
CURRENT_FIX_DURATION	integer	Duration of the current fixation	SR Eyelink
CURRENT_FIX_END	integer	Trial time when the current fixation ends	SR Eyelink
CURRENT_FIX_START	integer	Trial time when the current fixation starts	SR Eyelink

CURRENT_FIX_X	double	X coordinate of the current fixation	SR Eyelink
CURRENT_FIX_Y	double	Y coordinate of the current fixation	SR Eyelink
CompPort	integer	Screen location of Competitor image	E-Prime
Condition	integer	Trial condition (practice, associate, filler, taxonomic)	E-Prime
TargetLoc	integer	Screen location of Target image	E-Prime

```
summary(gaze)

##     Subject     CURRENT_FIX_PUPIL CURRENT_FIX_DURATION
CURRENT_FIX_END
##  9160   :1109   Min.   :  36.0    Min.   :   2.0       Min.   :
15622.0
##  9196   : 897   1st Qu.: 122.0    1st Qu.: 140.0       1st Qu.:
8919.5
##  9115   : 882   Median : 165.0    Median : 210.0       Median :
1886.0
##  9187   : 839   Mean   : 176.3    Mean   : 279.6       Mean   :
1958.0
##  9061   : 787   3rd Qu.: 201.0    3rd Qu.: 328.0       3rd Qu.:
2614.5
##  9171   : 786   Max.   :9144.0    Max.   :2660.0
Max.   :26184.0
##  (Other):5616

##  CURRENT_FIX_START CURRENT_FIX_X     CURRENT_FIX_Y       CompPort

##  Min.   :    4     Min.   :-3270.0   Min.   :-3270.0   image1:2794

##  1st Qu.:  650     1st Qu.:  234.5   1st Qu.:  173.5   image2:2762

##  Median : 1562     Median :  510.9   Median :  362.7   image3:2716

##  Mean   : 1680     Mean   :  510.5   Mean   :  354.0   image4:2644
```

```
##  3rd Qu.: 2334     3rd Qu.:  799.7   3rd Qu.:  522.7
##  Max.   :25848     Max.   : 3270.0   Max.   : 3270.0
##
##      Condition     TargetLoc         ACC              RT
##  associate:3059   image1:2769   Min.   :0.0000   Min.   : 2236
##  filler   :3010   image2:2891   1st Qu.:1.0000   1st Qu.: 2957
##  practice :1702   image3:2611   Median :1.0000   Median : 3237
##  taxonomic:3145   image4:2645   Mean   :0.9898   Mean   : 3631
##                                 3rd Qu.:1.0000   3rd Qu.: 3687
##                                 Max.   :1.0000   Max.   :26105
##
##      Target     TargetLocation
##  barn   : 213   1:2769
##  walker : 194   2:2891
##  acorn  : 184   3:2611
##  bandaid: 184   4:2645
##  pillow : 181
##  falcon : 180
##  (Other):9780
```

Parsing areas of interest

The following preprocessing assumes that the interest areas (locations of objects) were static and that the fixation report includes columns indicating the location of each object for each trial. For this example, the objects were always presented in the four corners of the screen, though which object was in which corner was randomized. The four possible image locations are labeled as image1, image2, image3, and image4. The `TargetLoc` variable identifies which of those locations was the target object and the `CompPort` variable identifies which of those locations was the critical semantically related competitor. The gaze position was recorded in terms of (x,y) coordinates. In order to determine which (if any) of the objects were being fixated, first identify the locations of the target and competitor images, then use gaze coordinates to determine which image location (if any) was being fixated, then compare gaze location to target and competitor locations. If gaze location has already been coded in terms of interest areas (many experiment programs do this dynamically, as the data are being collected), then this step can be skipped.

First, extract the numbered location of the target and competitor in order to match the output of the `assign_aoi` function, which will assign a numbered area of interest for each fixation that falls within a defined area of interest (by default, 400x300 rectangles in the corners of the screen). This sub-step is somewhat specific to how image locations were labeled in this particular experiment, where the image location is the 6th character in the location string (e.g., image2), so that is the value that needs to be extracted:

```
gaze$TargetLocation <- as.numeric(substr(gaze$TargetLoc, 6, 6))
gaze$CompLocation <- as.numeric(substr(gaze$CompPort, 6, 6))
```

Then match fixation locations to areas of interest (AOI) based on screen coordinates:

```
gaze_aoi <- assign_aoi(gaze)
summary(gaze_aoi)

##     Subject     CURRENT_FIX_PUPIL CURRENT_FIX_DURATION
CURRENT_FIX_END
##  9160   :1109   Min.   :  36.0    Min.   :   2.0       Min.   :
22822.0
##  9196   : 897   1st Qu.: 122.0    1st Qu.: 140.0       1st Qu.:
919.5
##  9115   : 882   Median : 165.0    Median : 210.0       Median :
1886.0
##  9187   : 839   Mean   : 176.3    Mean   : 279.6       Mean   :
1958.0
##  9061   : 787   3rd Qu.: 201.0    3rd Qu.: 328.0       3rd Qu.:
2614.5
##  9171   : 786   Max.   :9144.0    Max.   :2660.0
Max.   :26184.0
##  (Other):5616

##  CURRENT_FIX_START CURRENT_FIX_X     CURRENT_FIX_Y       CompPort

##  Min.   :    4     Min.   :-3270.0   Min.   :-3270.0   image1:2794

##  1st Qu.:  650     1st Qu.:  234.5   1st Qu.:  173.5   image2:2762

```

```
##  Median : 1562     Median :  510.9   Median :  362.7   image3:2716
##  Mean   : 1680     Mean   :  510.5   Mean   :  354.0   image4:2644
##  3rd Qu.: 2334     3rd Qu.:  799.7   3rd Qu.:  522.7
##  Max.   :25848     Max.   : 3270.0   Max.   : 3270.0
##
##      Condition     TargetLoc         ACC               RT
##  associate:3059   image1:2769   Min.   :0.0000   Min.   : 2236
##  filler   :3010   image2:2891   1st Qu.:1.0000   1st Qu.: 2957
##  practice :1702   image3:2611   Median :1.0000   Median : 3237
##  taxonomic:3145   image4:2645   Mean   :0.9898   Mean   : 3631
##                                 3rd Qu.:1.0000   3rd Qu.: 3687
##                                 Max.   :1.0000   Max.   :26105
##
##      Target     TargetLocation  CompLocation        AOI
##  barn   : 213   Min.   :1.00   Min.   :1.000   Min.   :0.000
##  walker : 194   1st Qu.:1.00   1st Qu.:1.000   1st Qu.:0.000
##  acorn  : 184   Median :2.00   Median :2.000   Median :2.000
##  bandaid: 184   Mean   :2.47   Mean   :2.477   Mean   :1.721
##  pillow : 181   3rd Qu.:3.00   3rd Qu.:3.000   3rd Qu.:3.000
##  falcon : 180   Max.   :4.00   Max.   :4.000   Max.   :4.000
##  (Other):9780                                  NA's   :1040
```

Now determine which object was being fixated by matching AOI codes with target and competitor locations:

```
gaze_aoi$Targ <- gaze_aoi$AOI == gaze_aoi$TargetLocation
gaze_aoi$Comp <- gaze_aoi$AOI == gaze_aoi$CompLocation
gaze_aoi$Unrelated <-
      ((gaze_aoi$AOI != as.numeric(gaze_aoi$TargetLocation)) &
      (gaze_aoi$AOI != as.numeric(gaze_aoi$CompLocation)) &
      (gaze_aoi$AOI != 0) & !is.na(gaze_aoi$AOI))
```

Fixations to bins

Fixations can start and end at any time point, but most analysis strategies require aligned, equally-spaced time bins. The `binify_fixations` function will unpack the set of fixations into a fixation time series consisting of standardized time bins with a size specified by the user (default is 20ms). In addition, it will drop columns that are no longer necessary – the fixation start and end time and duration will no longer be needed, nor will the gaze position coordinates, since gaze position has now been recoded from coordinates to objects. The user needs to specify a list columns that should be kept after the binning is done. Converting fixations to bins can be somewhat slow.

```
gaze_bins <- binify_fixations(
  gaze = gaze_aoi,
  keepCols = c("Subject", "Target", "Condition", "ACC",
               "RT", "Targ", "Comp", "Unrelated"))
```

Aggregate Data

The specifics of data organization and aggregation will depend on the design and hypotheses of the specific study. For this example, the fixation locations need to be "gathered" from separate columns into a single column (see Supplemental Figure for a demonstration of this) and "NA" values need to be re-coded as not-fixations:

```
gaze_obj <- gather(gaze_bins,
                   key = "Object", value = "Fix",
                   Targ, Comp, Unrelated, factor_key = TRUE)
# recode NA as not-fixating
gaze_obj$Fix <- replace(gaze_obj$Fix, is.na(gaze_obj$Fix), FALSE)
summary(gaze_obj)
```

```
##    FixationID       timeBin           Subject              Target

##   Min.   :    1   Min.   :   1.00   9115   : 43680   barn      :
9552
##   1st Qu.: 2732   1st Qu.:  45.00   9160   : 38553   walker    :
8283
##   Median : 5295   Median :  88.00   9061   : 36645   bandaid   :
8256
##   Mean   : 5458   Mean   :  95.09   9156   : 35202   acorn     :
8019
##   3rd Qu.: 8293   3rd Qu.: 130.00   9171   : 32793   soda      :
7926
##   Max.   :10916   Max.   :1310.00   9092   : 32289   paintbrush:
7839
##                                     (Other):265791
```

```
(Other)   :435078
##      Condition           ACC               RT              Time
##  associate:135507   Min.   :0.0000   Min.   : 2236   Min.   :   20
##  filler   :135375   1st Qu.:1.0000   1st Qu.: 2947   1st Qu.:  900
##  practice : 75618   Median :1.0000   Median : 3229   Median : 1760
##  taxonomic:138453   Mean   :0.9895   Mean   : 3641   Mean   : 1902
##                     3rd Qu.:1.0000   3rd Qu.: 3673   3rd Qu.: 2600
##                     Max.   :1.0000   Max.   :26105   Max.   :26200
##
##       Object          Fix
##  Targg     :161651   Mode :logical
##  Comp     :161651   FALSE:379285
##  Unrelated:161651   TRUE :105668
```

In the final stage of preprocessing, the error and practice trials can be removed and the time window can be restricted, to make the data ready for aggregation. For this example, we group the trials by Subject, Condition, and Object type to calculate number of valid trials in each cell. Then also group by time bin to calculate the number of object fixations and mean fixation proportion in each time bin; that is, the time course of fixation. These are the subject-by-condition time courses that would go into an analysis.

```
gaze_subj <- gaze_obj %>%
  # keep only correct-response trials, exclude practice condition, and analyze time points only up to 3500ms after trial onset
  filter(ACC == 1, Condition != "practice", Time < 3500) %>%
  # calculate number of valid trials for each subject-condition
  group_by(Subject, Condition, Object) %>% # for every unique combination of Subject, Condition, and Object…
  mutate(nTrials = length(unique(Target))) %>% # count the number of trials

  ungroup() %>%
  # calculate number of fixations counts and proportions
  group_by(Subject, Condition, Object, Time) %>% # for every unique
```

```
combination of Subject, Condition, and Object in each time bin
  summarize(sumFix = sum(Fix), # number of fixations
            nTrials = unique(nTrials), # number of trials
            meanFix = sum(Fix)/unique(nTrials)) # fixation proportion
# there were two unrelated objects, so divide those proportions by 2
gaze_subj$meanFix[gaze_subj$Object == "Unrelated"] <-
  gaze_subj$meanFix[gaze_subj$Object == "Unrelated"] / 2
summary(gaze_subj)
```

```
##     Subject          Condition          Object           Time     
##  9061   : 1566   associate:7800   Targ     :7790   Min.   :  20  
##  9062   : 1566   filler   :7758   Comp     :7790   1st Qu.: 880  
##  9092   : 1566   practice :   0   Unrelated:7790   Median :1740  
##  9115   : 1566   taxonomic:7812                    Mean   :1742  
##  9146   : 1566                                     3rd Qu.:2600  
##  9153   : 1566                                     Max.   :3480  
##  (Other):13974                                                   
##      sumFix          nTrials         meanFix       
##  Min.   : 0.000   Min.   :19.00   Min.   :0.00000  
##  1st Qu.: 0.000   1st Qu.:20.00   1st Qu.:0.00000  
##  Median : 2.000   Median :20.00   Median :0.07895  
##  Mean   : 3.495   Mean   :19.87   Mean   :0.15186  
##  3rd Qu.: 5.000   3rd Qu.:20.00   3rd Qu.:0.20000  
##  Max.   :20.000   Max.   :20.00   Max.   :1.00000  
##
```

Plot fixation time course

After the fixations have been assigned to the object type and converted to time bins, they are ready for visualization and statistical analysis. Below is a plot of the time course of fixation proportions for each target type.

```
ggplot(gaze_subj, aes(Time, meanFix, color = Object)) +
  facet_wrap(~ Condition) +
  stat_summary(fun.y = mean, geom = "line") +
  geom_vline(xintercept = 1300) +
  annotate("text", x=1300, y=0.9, label="Word onset", hjust=0)
```

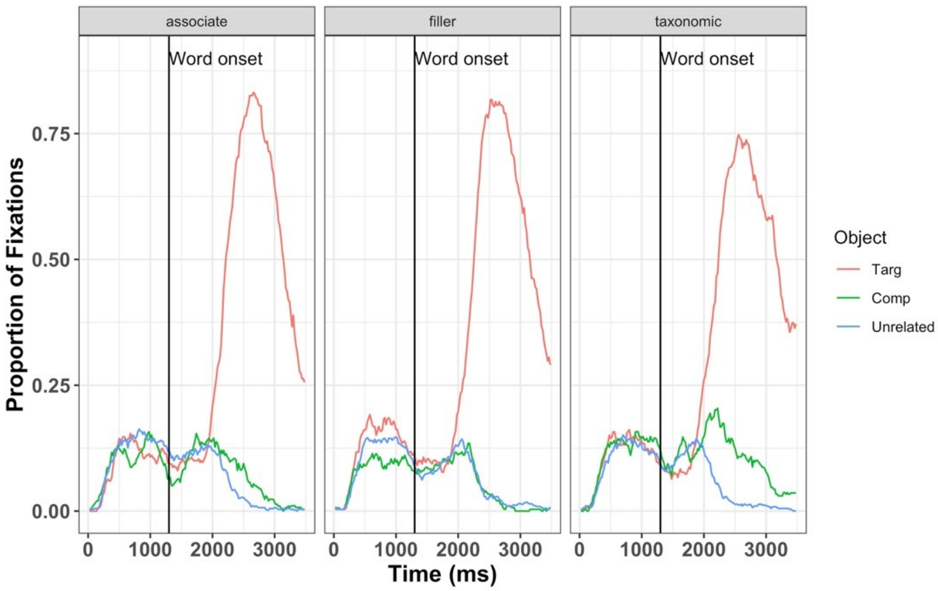


Figure 3. Time course of fixation proportions by condition. These data have been pre-processed and are ready for statistical analysis.

Preprocessing Pupil Data from a Lexical Decison Task

Recent advances in eye-tracking technology have lead to a burgeoning interest in cognitive pupillometry (i.e., measurement of changes in pupil size as it relates to higher-level processing). According to a recent PubMed search, the number of studies employing pupillometry has grown exponentially since the first modern boom more than a half a century ago (Kret & Sjak-Shie, 2018). The reason for this is quite simple: pupil size has been shown to be a reliable and valid index of mental effort or arousal across many domains, including word recognition (Geller, Still, & Morris, 2016), normal and impaired auditory perception (Zekveld et al., 2018), attention allocation (Karatekin, Couperus, & Marcus, 2004), working memory load (Granholm, Asarnow, Sarkin, & Dykes, 1996; Van Gerven, Paas, Van Merriënboer, & Schmidt, 2004), face perception (Goldinger, He, and Papesh, 2009), and general cognitive processing (Murphy et al., 2014). While there are a number of good open-source programs available in R to analyze pupil data (see Forbes, 2019; Tsukahara, 2018), there are not many walkthroughs demonstrating how to go from raw data to fully pre-processed data. A recent methods review by Winn et al. (2018) describes and illustrates general principles like blink detection, interpolation, and filtering. The gazeR package includes functions for implementing these steps and here we demonstrate their use.

To demonstrate analysis of pupil data, we will be using an example data set containing data from a lexical decision task. In this task, participants (*N*=41) judged the lexicality of printed and cursive stimuli while pupil diameter was recorded. Because cursive stimuli are non-segmented and could be ambiguous, it was predicted that recognizing cursive stimuli would require more effort than printed words (cf., Barnhart & Goldinger, 2010; Geller, Still, Dark, & Carpenter, 2018), resulting in larger pupil dilation.

Preprocessing pupil data requires the following steps:

(1) Read in data

(2) De-blinking

- Extending blinks
- Interpolation

(4) Smoothing

(5) Baseline correction

(6) Re-scaling

(7) Artifact Rejection

- Missing data
- Unlikely pupil values

- Median absolute deviation (MAD)

(8) Trial Clipping

(9) Decimating/Downsampling

(10) Aggregation

Reading in Pupil Data

In order for the pupil functions to work properly, the Sample Report must be generated with the columns below. The functions will not work if these columns are not present in the Sample Report. Other columns should be included if needed.

Table 1. Variables Needed to Process Pupil Data

Names
RECORDING_SESSION_LABEL
TRIAL_INDEX
AVERAGE_IN_BLINK, RIGHT_IN_BLKINK, or LEFT_IN_BLINK
TIMESTAMP
AVERAGE_PUPIL_SIZE, RIGHT_PUPIL_SIZE, or LEFT_PUPIL
SIZE
IP_START_TIME
SAMPLE_MESSAGE

If you generated separate sample reports for each participant, the function `merge_pupil` will take all your pupil files from a folder path and merge them together. It will also rename variables, make all variable names lowercase, and add a new column, `time`, which places time in ms instead of tracker time. You must first specify a list of pupil data files, then you can call the `merge_pupil` function to aggregate your data. Depending on the number of subjects and the sampling rate at experiment runtime, this could take a few minutes. There are two arguments, `blink_colname` and `pupil_colname`. It is important you specify what these variables are called in your data set so the pipeline runs smoothly. In our example dataset, we used the AVERAGE_IN_BLINK and AVERAGE_PUPIL_SIZE columns.

```
# where to find all your pupil files
file_list <- list.files(path = '', pattern = ".xls")
pupil_files <- merge_pupil(
  file_list,
  blink_colname = “AVERAGE_IN_BLINK”,
  pupil_colname = “AVERAGE_PUPIL_SIZE”
)
```

Due to processing constraints, we are using a Sample Report that includes data from a few participants. If you would like to try out the `merge_pupil` function you can download all the participant files on Open Science Framework (OSF) here: https://osf.io/fzu38/. While reading in the data is pretty fast (even with many participants), some of the functions performed on the data can be computationally intensive.

```
#download Sample Report from Github
pupil_path <- system.file("extdata", "Pupil_file1.xls", package =
"gazer")
#read in data
pupil_files <- read.table(pupil_path)
```

Table 3. Pupil Data Description and Structure

Variable	Class	Contents	Source
subject	integer	Label of the data file	SR Eyelink
trial	integer	Trial number	SR Eyelink
blink	integer	Whether eye was in blink	SR Eyelink
pupil	integer	pupil size on the current sample	SR Eyelink
accuracy	integer	0=incorrect; 1=correct	SR Eyelink

cb	integer	counterbalance list	SR Eyelink
key_pressed	integer	response made	SR Eyelink
rt	integer	condition (word, nonword transposed letter, 2L substition nonword)	SR Eyelink
alteration	integer	Trial condition (practice, associate, filler, taxonomic)	SR Eyelink
block	integer	Block number	SR Eyelink
item	character	item presented	SR Eyelink
response	integer	button pressed	SR Eyelink
script	integer	condition (cursive, type-print)	SR Eyelink
target	character	eye in saccade	SR Eyelink
average_in_saccade	integer	Start time of the interest period	SR Eyelink
ip_start_time	integer	Start time (in milliseconds since EyeLink tracker was Eyelink	SR Eyelink

sample_message	character	Message text printed out during current sample	SR Eyelink
timestamp	integer	Time lapsed (in milliseconds) since eye-tracker started	SR Eyelink
time	integer	ip_start_time - timestamp	SR Eyelink

Behavioral Data (Optional)

If you are also interested in analyzing behavioral data (RTs and accuracy), the `behave_data` function will cull the important behavioral data from the Sample Report. The function will return a data frame without errors when `omiterrors=TRUE` or a data frame with errors for accuracy/error analysis when `omiterrors=FALSE`. The columns relevant for your experiment need to be specified within the `behave_col` names argument. This function does not eliminate outliers; you must use your preferred method. Grange's (2015) `trimr` package implements multiple standard methods of outlier exclusion (https://github.com/JimGrange/trimr).

```
##      subject  script alteration trial     target accuracy   rt
block cb
## 1        10b   print       word     1 sprigp.png        1 2539
0  2
## 960      10b cursive       nwtl     2  nypmh.png        1 3254
0  2
## 2117     10b Cursive       nwtl     3 seivep.png        0 1755
0  2
## 2882     10b cursive       word     4  mourn.png        1 2435
0  2
## 3821     10b Cursive       word     5  noisy.png        1 2200
1  2
## 5197     10b Cursive       word     6  ridge.png        1 1952
1  2
```

For this example, we will exclude participants with overall accuracy lower than 75% and items with accuracy below 60%. Using the file generated above with `omiterrors=FALSE`, we can calculate subject and item accuracy, merge those values into the main data set, and use them as exclusion criteria.

```
Itemacc <- behave_data %>%
  group_by(target) %>%
  summarise(
    # overall item accuracy and word condition only
    meanitemacc = mean(accuracy[block>0 & alteration=="word"])
  )

subacc <- behave_data %>%
  group_by(subject) %>%
  summarise(
    #subject accuracy and word condition only
    meansubacc = mean(accuracy[block > 0 & alteration == "word"])
  )

dataraw1 <- merge(pupil_files, itemacc) # merge into main ds
dataraw2 <- merge(dataraw1, subacc) # merge into main ds
```

We can now restrict preprocessing to valid trials by removing practice blocks, trials with incorrect responses, conditions that are not words, subjects with accuracy below 75%, and items with accuracy below 60%.

```
pupil_files1 <- dataraw2 %>%
# filter out practice blocks, incorrect responses, nonword trials, low
item and subj acc
  filter(
    block > 0, accuracy == 1, alteration == "word",
     meanitemacc >= .60, meansubacc >= .75
  ) %>%
  arrange(subject, target, trial, time)
```

Pupil Preprocessing is now ready to begin!

De-blinking

An imporatant first step in preprocessing pupil data is de-blinking. A major artifact in pupil data comes from blinking. When the eye blinks, the pupil momentarily becomes smaller as it is occluded more and more by the eyelids, making computing the center of the pupil difficult. Eye-trackers interpret this as a fast shift in pupil position and will classify it as a saccade. Additionally, the estimate of pupil size will rapidly decrease as the pupil occupies less of the camera image. This process happens in reverse (albeit a bit more slowly) as the eye is opening, so blinks are always flanked by a saccade artifact. Occasionally there will be some additional artifacts, such as short fixations preceding or following the blink. It is thus advisable to de-blink the data, which involves identifying blinks, removing them, and then interpolating data during the blink period and even across a longer segment that extends before and after the blink. Identifying blinks is rather trivial as the EyeLink records contain a blink column with 0s or 1s denoting absence or presence of a blink. Less trivial is deciding how many data points you remove before and after the blink. It has generally been recommended that data 100 ms before and after the blink should be eliminated. The gazeR package contains several functions for dealing with blinks. If you are exporting files from SR, there is an option to extend blinks within Data Viewer. There are several ways one can deal with blinks (see Hershman, Henik, & Cohen, 2018). One method is to eliminate all blinks from a trial. This is generally not recommended as it can eliminate too much data, resulting in a loss of power. A more acceptable approach, and the one implemented in gazeR, is to extend the time window around the blinks so the interpolation starts 100-200 ms before the blink and after the blink (Nyström, Hooge, & Andersson, 2016; Satterthwaite et al., 2007). Extending the time window around the blinks eliminates spurious samples caused by the closing and opening of the eyelids. If you have not done this before exporting into R, you can use the `extend_blinks` function. The fillback argument extends blinks back in time and the fillforward argument extends blinks forward in time. This function is robust to different sampling rates — make sure you specify the tracker sampling rate in the `hz` argument. For this experiment, the tracker sampled at 250Hz (once every 4 ms) and blinks were extended 100 ms forward and backward in time.

```
pup_extend<- pup_files1 %>%
  group_by(subject, trial) %>%
  mutate(extendpupil=extend_blinks(pupil, fillback=100,
fillforward=100, hz=250))
```

Interpolation

Missing data stemming from blinks or failure of the eye tracker need to be interpolated. The `interpolate_pupil` function searches the data and reconstructs the pupil size for each trial from the relevant samples using either linear interpolation (Bradley, Miccoli, Escrig, & Lang, 2008; Cohen et al., 2015; Siegle, Steinhauer, Carter, Ramel, & Thase, 2003) or cubic-spline interpolation (Mathôt, 2018). Considering the short duration of blinks and the relatively low speed of blinks, the choice of linear versus cubic interpolation will ultimately have negligible effect. If extendblinks = FALSE, samples with blinks are turned into "NA"s and are then interpolated linearly or by cubic interpolation. This function returns a tibble with a column called `interp` which contains interpolated values from the pupil column in your data (e.g., average, left, or right pupil size). As an important note, if the Data Viewer was used to extend blinks, the `extendblinks` argument should be set to FALSE. If `gazer::extend_blinks` was used, the `extendblink` argument should be set to TRUE. It is important to note that SR only extends the blink column and does not set pupil size estimates during blinks to "NA" in the Sample Report. For this example, we will set `extendblinks` to TRUE and use linear interpolation. You can use cubic interpolation by changing type to "cubic."

```
pup_interp <- interpolate_pupil(
  pup_extend,
  extendblinks = TRUE,
  type = "linear")

## Performing linear interpolation
```

It is a good idea to check that the interpolation did what it was supposed to do. The plot below shows data from one trial with artifacts removed, the observed data are shown in black and the interpolated data are shown in green. Looks good!

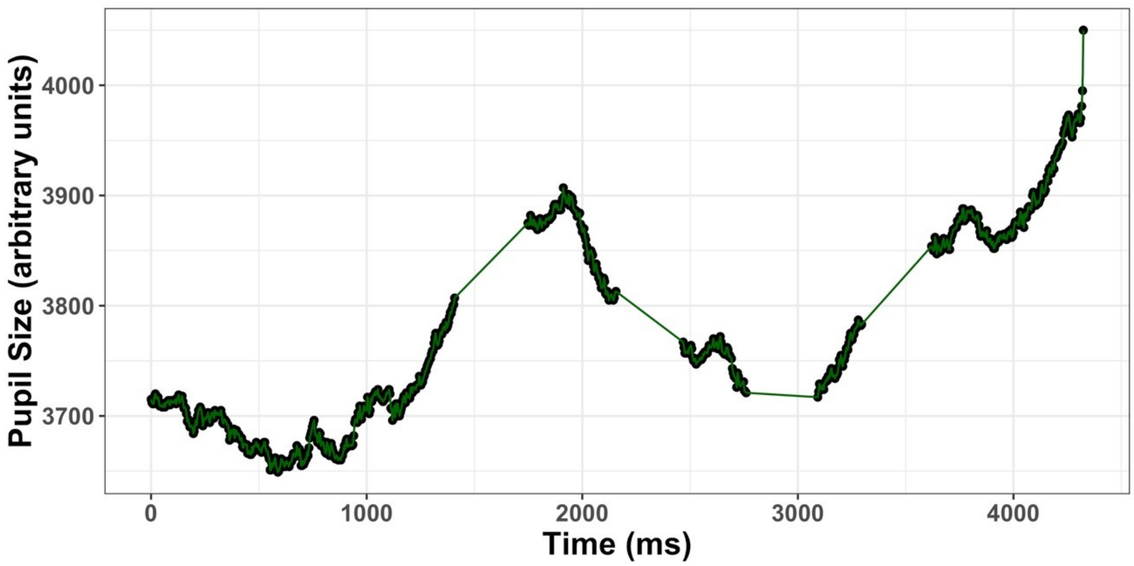


Figure 4. Linear interpolation for one trial

Smoothing

Pupil data can be extremely noisy! There are many ways to smooth pupil data. Two common methods are implemented in gazeR: n-point moving average and a hanning filter. To smooth the data using a n-point moving average, call the `moving_average_pupil` function, and specify the column that contains the interpolated pupil values and the size (in samples) of the moving average window. In this example, we use a 5-point moving average (n=5). The variable `movingavgpup` is returned with the smoothed pupil data. Low-pass filtering is something that might be included in a future update to the package.

```
rolling_mean_pupil_average <- as.data.frame(pup_interp) %>% #must be in a data.frame
  select(
    subject, trial, target, pupil, script, alteration,
    time, interp, sample_message
  ) %>%

  mutate(movingavgpup = moving_average_pupil(interp, n = 5))
```

Baseline correction

To control for variability in overall pupil size arising from non-task related (tonic) state of arousal, baseline correction is commonly used (but see Attard-Johnson, Ó Ciardha, & Bindemann, 2019). The two most popular types of baseline correction to identify task-evoked *dilation* are subtractive (pupil size - baseline) and divisive (pupil size / baseline). Subtractive baseline correction is more common in the literature (cf., Beatty, 1982; Laeng et al., 2012; Zekveld, Koelewijn, & Kramer, 2018), and this practice has been supported on the basis of a study by Reilly, Kelly, Kim, Jett, and Zuckerman (2018) that argued for linearity of the pupil response, independent of baseline size[2]. The `baseline_correction_pupil` function finds the median pupil size during a specified baseline period for each trial and performs a subtraction baseline correction by default (see Mathôt et al., 2018, for argument that baseline correction should be done using the median, and not the mean, baseline value). By changing the baseline_method argument to “div”, you will get proportion change from baseline. In this example, subtractive baseline correction is applied to pupil size in arbitrary units (pupil_colnames = "movingavgpup") though the same can be done for pupil size in mm or *z*-score. The baseline window is the 500ms immediately preceding stimulus onset, which in this study is 500-1000ms after trial onset.

[2] Reilly et al. varied luminance in order to elicit different baseline sizes, but that is not the typical source of baseline pupil size differences. Tonic baseline pupil size differences due to arousal, age, or other variables may affect the range of dilation reactivity in ways that differ from changes that are elicited by changes in luminance. Additonally, Wang et al. (2018) suggested that brighter lighting condition elicit *larger* dilations, on account of suppression of the parasympathetic suppressive influence on dilations. These factors can be used to motivate divisive baseline correction.

```
baseline_pupil <- baseline_correction_pupil(
  rolling_mean_pupil_average,
  pupil_colnames = "movingavgpup",
  baseline_window = c(500, 1000),
  baseline_method = 'sub'
)
## Calculating baseline

## Calculating median baseline from:500-1000

## Merging baseline

## Performing subtractive baseline correction


baseline_pupil

## # A tibble: 11,031 x 11
## # Groups:   subject, trial, time [11,031]
##    subject trial  time baseline target script alteration interp
##    <fct>   <int> <int>    <dbl> <fct>  <fct>  <fct>       <dbl>
##  1 10b         5   680    4130. noisy… Cursi… word         4373
##  2 10b         5   684    4253. noisy… Cursi… word         4375
##  3 10b         5   688    4379. noisy… Cursi… word         4374
##  4 10b         5   692    4382. noisy… Cursi… word         4382
##  5 10b         5   696    4386  noisy… Cursi… word         4389
##  6 10b         5   700    4390. noisy… Cursi… word         4392
##  7 10b         5   704    4395  noisy… Cursi… word         4393
##  8 10b         5   708    4399. noisy… Cursi… word         4396
##  9 10b         5   712    4403. noisy… Cursi… word         4405
## 10 10b         5   716    4407  noisy… Cursi… word         4408
## # … with 11,021 more rows, and 3 more variables: sample_message
<fct>,
## #   pupil1 <dbl>, baselinecorrectedp <dbl>
```

Re-Scaling

So far, the analysis steps have used arbitrary pupil units. It is advised that these be transformed into a standardized unit in order to make comparisons between individuals. Among the numerous options that have been used, there are z-scores (see Cohen, Moyal, & Henik, 2015; Einhauser, Stout, Koch, & Carter, 2008; Kang & Wheatley, 2015), absolute changes in mm (e.g., Beatty, 1982; Geller, Landrigan, & Mirman, 2019; Geller et al., 2016), proportional change relative to baseline (Winn, 2016), and absolute change relative to dynamic range of pupil reactivity elicited by the light reflex (Piquado, Isaacowitz, & Wingfield, 2010). To convert arbitrary pupil size to mm, we measured the scaling factor by running a short experiment with an artificial pupil (5 mm in size) and calculated the average pupil size in arbitrary units. At a fixed camera-to-pupil distance of 90 cm, the 5mm pupil was coded as 5570.29 arbitrary pixel units. This information was entered into the equation below to convert arbitrary units to mm. Specifically, the smoothed pupil size value is multiplied by 5/5570.29 to re-scale the values to mm.

```
timebinsmm <- rolling_mean_pupil_average  %>%
  mutate(pupilmm = (movingavgpup * 5)/5570.29)
```

Alternatively, the arbitrary pupil units can be converted to a *z*-score using the `scale` function.

```
timebinsz<- rolling_mean_pupil_average %>%
  group_by(subject, trial) %>%
  mutate(pupilz = scale(movingavgpup))
```

Artifact Rejection

Missingness. The `count_missing_pupil` function will remove subjects and items that have a large amount of missing data – the threshold for “a large amount” is specified by the researcher. It has been recommended by Winn et al. (2018) that a reasonable threshold is 20%, but that the exact importance of missing data might be weighted by specific timing landmarks in the experiment trials. For this example, we have set the `missingthresh` argument to .2. The `count_missing_pupil()` function returns the percentage of subjects and trials that have been excluded for reporting.

```
pup_missing <- count_missing_pupil (baseline_pupil, missingthresh =
.2)
```

```
## % trials excluded:0.011
## subjects taken out:
```

Spurious pupil values. Unlikley pupil values that are too small and too large should be removed from the data (Mathôt et al., 2018; Winn et al., 2018). Mathôt (2018) recommended against removing data based on a subject-independent fixed criterion (e.g., above or below a SD cut-off or a specified lower and upper pupil boundary). This is due to the inherent heterogeneity of pupil sizes across experiments. Instead, Mathôt (2018) recommend visual inspection to determine unlikely pupil values. This can be done using a simple histogram to plot the pupillometric data. Based on the histogram below, it seems reasonable to remove pupil sizes less than 2500 and greater than 5000.

```
puphist <- ggplot(pup_extend, aes(x = extendpupil)) +
  geom_histogram(aes(y = ..count..), colour = "green", binwidth = 0.5) +
  geom_vline(xintercept = 2500, linetype="dotted") +
  geom_vline(xintercept = 5100, linetype="dotted") +
  xlab("Pupil Size") +
  ylab("Count") +
  theme_bw()

print(puphist)
```

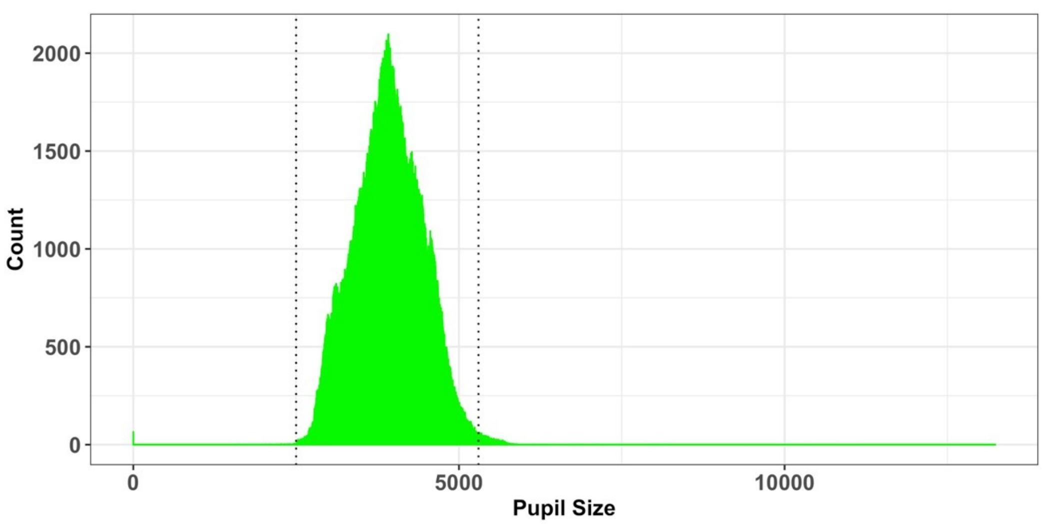


Figure 5. Histogram of recorded pupil sizes throughout experiment for all 41 participants.

```
pup_outliers <- pup_missing %>%
  # based on visual inspection
  dplyr::filter(interp  >= 2500, interp <= 5100)
```

Median absolute deviation (MAD). After interpolation, it is a good idea to perfrom a second pass on your data to make sure that the data is not contaminated by rapid pupil size disturbances.   These artifacts can be detected using the median absolute deviation (Kret & Sjak-Shie, 2018). The `speed_dilation` function calculates the normalized dilation speed, which is the absolute change in pupil size between samples divided by the temporal separation between them. To detect outliers, the median absolute deviation is calculated from the speed dilation variable, multiplied by a constant (in this case 16), and added to the median dilation speed variable using the `calc_mad` function–values above this threshold are then removed.

```
mad_removal <-pup_outliers  %>%
  group_by(subject, trial) %>%
  mutate(speed=speed_pupil(interp,time)) %>%
  mutate(MAD=calc_mad(speed, n = 16)) %>%
  filter(speed < MAD)
```

Event Time Alignment

In most psychological experiments, each trial includes several events. In the example experiment, each trial began with a fixation screen (small cross in the center of the screen) and the stimulus of interest appeared on screen 1s after trial onset. These events are documented in the data file: the onset of the target is denoted by the trial message “target.” We can use this information to align the data so that time=0 corresponds to stimulus onset (i.e., the analysis window of interest) rather than trial onset. The `onset_pupil` function performs this alignment using three arguments: time column, sample message column, and the event of interest (“target” in our example). In the output below, we can see below that our experiment now starts at zero, when the target was displayed on screen.

```
baseline_pupil_onset <- baseline_pupil %>%
  group_by(subject, trial) %>%
  mutate(
    time_zero = onset_pupil (time, sample_message, event =
c("target"))
  ) %>%
  ungroup() %>%
  filter(time_zero >= 0, time_zero <= 3000) %>%
  select(
    subject, trial, time, script, time_zero,
    sample_message, baselinecorrectedp
  )

baseline_pupil_onset
```

```
## # A tibble: 66,126 x 7
##    subject trial  time script  time_zero sample_message
baselinecorrectedp
##    <fct>   <int> <int> <fct>       <int> <fct>
<dbl>
##  1 10b        11   348 Cursive         0 target
-11.9
##  2 10b        11   352 Cursive         4 <NA>
-15.5
##  3 10b        11   356 Cursive         8 <NA>
-19.1
##  4 10b        11   360 Cursive        12 <NA>
-24.1
##  5 10b        11   364 Cursive        16 <NA>
-28.5
##  6 10b        11   368 Cursive        20 <NA>
-32.1
##  7 10b        11   372 Cursive        24 <NA>
-34.5
##  8 10b        11   376 Cursive        28 <NA>
-35.7
##  9 10b        11   380 Cursive        32 <NA>
-35.9
## 10 10b        11   384 Cursive        36 <NA>
-37.5
```

Downsampling/Decimation

If the data are recorded at a relatively high sampling frequency (e.g., 250Hz in this example), it may be useful to aggregate the the data into time bins that are somewhat larger than the sample rate (users can specify a time bin size to use). The `downsample_pupil` function takes your data and a specified bin length (in ms) as arguments and returns a tibble with a column called timebins.

```
timebins1 <- downsample_pupil(baseline_pupil_onset, bin.length=200)

timebins1
```

```
## # A tibble: 66,126 x 8
##    subject trial  time script time_zero sample_message
baselinecorrect…
##    <fct>   <int> <int> <fct>      <int> <fct>
<dbl>
##  1 10b        11   348 Cursi…         0 target                       -
11.9
##  2 10b        11   352 Cursi…         4 <NA>                         -
15.5
##  3 10b        11   356 Cursi…         8 <NA>                         -
19.1
##  4 10b        11   360 Cursi…        12 <NA>                         -
24.1
##  5 10b        11   364 Cursi…        16 <NA>                         -
28.5
##  6 10b        11   368 Cursi…        20 <NA>                         -
32.1
##  7 10b        11   372 Cursi…        24 <NA>                         -
34.5
##  8 10b        11   376 Cursi…        28 <NA>                         -
35.7
##  9 10b        11   380 Cursi…        32 <NA>                         -
35.9
## 10 10b        11   384 Cursi…        36 <NA>                         -
37.5
## # … with 66,116 more rows, and 1 more variable: timebins <dbl>
```

Aggregating Data

To further simplify the data, they can be aggregated to produce an average pupil diameter for each subject in each condition at each time bin.

```
agg_subject<- timebins1 %>%
  dplyr::group_by(subject, script,timebins) %>%
dplyr::summarise(aggbaseline=mean(baselinecorrectedp)) %>%
  ungroup()

## # A tibble: 80 x 4
##    subject script  timebins aggbaseline
##    <fct>   <fct>      <dbl>       <dbl>
##  1 10b     Cursive        0       16.0
##  2 10b     Cursive      200        3.03
##  3 10b     Cursive      400       -3.92
##  4 10b     Cursive      600       10.8
##  5 10b     Cursive      800       38.8
##  6 10b     Cursive     1000       74.8
##  7 10b     Cursive     1200      102.
##  8 10b     Cursive     1400      113.
##  9 10b     Cursive     1600      114.
```

Pupillary Data Visualization

After baseline-correction and aggregation, the data are ready for visualization and statistical analysis. The pre-processed data produced by gazeR are highly flexible and compatible with different visualization strategies. Below is a plot of the time course for the baseline-corrected pupillary response between cursive and type-print stimuli. A cursory look suggests that that recognizing cursive words resulted in a larger pupillary response at around 1600-2500ms.

```
data(cursive_new)

## # A tibble: 6 x 4
##   subject script  timebins aggbaseline
##   <chr>   <chr>      <dbl>       <dbl>
## 1 10b     cursive        0       15.7
## 2 10b     cursive      200        3.14
## 3 10b     cursive      400       -4.53
## 4 10b     cursive      600        6.63
## 5 10b     cursive      800       34.6
## 6 10b     cursive     1000       73.8

runningSE <- cursive_new %>%
  filter(timebins <= 3500) %>%
  split(.$timebins) %>%
  map(~Rmisc::summarySEwithin(data = ., measurevar = "aggbaseline",
withinvars = "script", idvar="subject"))
```

```
cur1 <- filter(cursive_new, timebins <= 3500)

WSCI <- map_df(runningSE, extract) %>%
  mutate(Time = rep(unique(cur1$timebins), each = 2))
    #Note, you'll have to change 2 to match the number of conditions

WSCI.plot <- ggplot(WSCI) + geom_line(aes(Time, aggbaseline,
linetype=script, color=script), size=3) +
  theme_bw() +
  labs(x = "Time (ms)",y = "Baseline-corrected pupil size (a.u)") +
  geom_hline(yintercept = 0,linetype = "dashed") +
  geom_ribbon(data = WSCI, aes(x=Time, ymin = aggbaseline-ci, ymax =
aggbaseline+ci, linetype=script, colour=script),  alpha = 0.3) +
  theme(axis.title.y=element_text(size = 14, face="bold"),
axis.title.x = element_text(size=14,   face="bold"),
axis.text.x=element_text(size = 12,
face="bold"),axis.text.y=element_text(size=12, face="bold"))

WSCI.plot
```

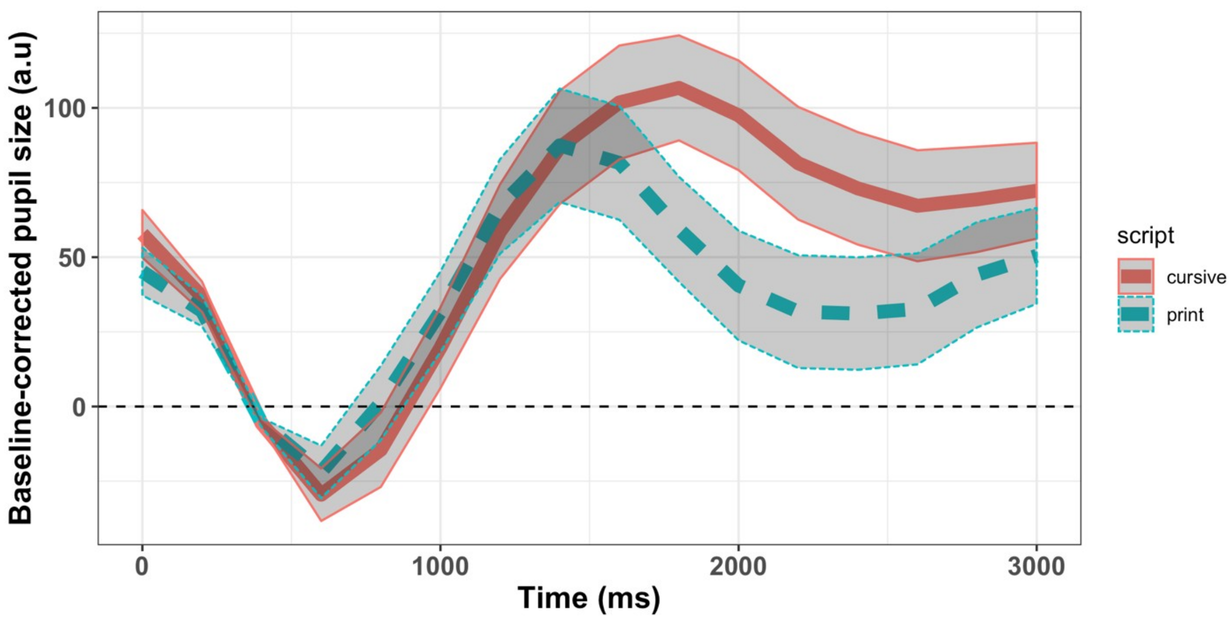


Figure 6. Pupillary time course as a function of script type. Ribbons denote 95% CIs.

In addition to pupillary time course, it is common to use summary measures: mean and max pupil size. Below you can see how to construct a graph based on mean and max pupil size using the *ggstatsplot* package (Patil, 2018).

```
data(cursive_new)
library(ggstatsplot)

mean_pup<-subset(cursive_new, timebins<=2500) %>%
  group_by(subject, script) %>%
  summarise(meanpup=mean(aggbaseline), maxpup=max(aggbaseline)) %>%
  ungroup()

mean<-ggstatsplot::ggwithinstats(
  data = mean_pup,
  x = script,
  y = meanpup,
  title = "Mean Pupil Size",
  xlab  = “Script”,           # turn off the default subtitle
  Ylab = ="Mean Change in Pupil Size (arbituary units)”,

)


plot(mean)
```

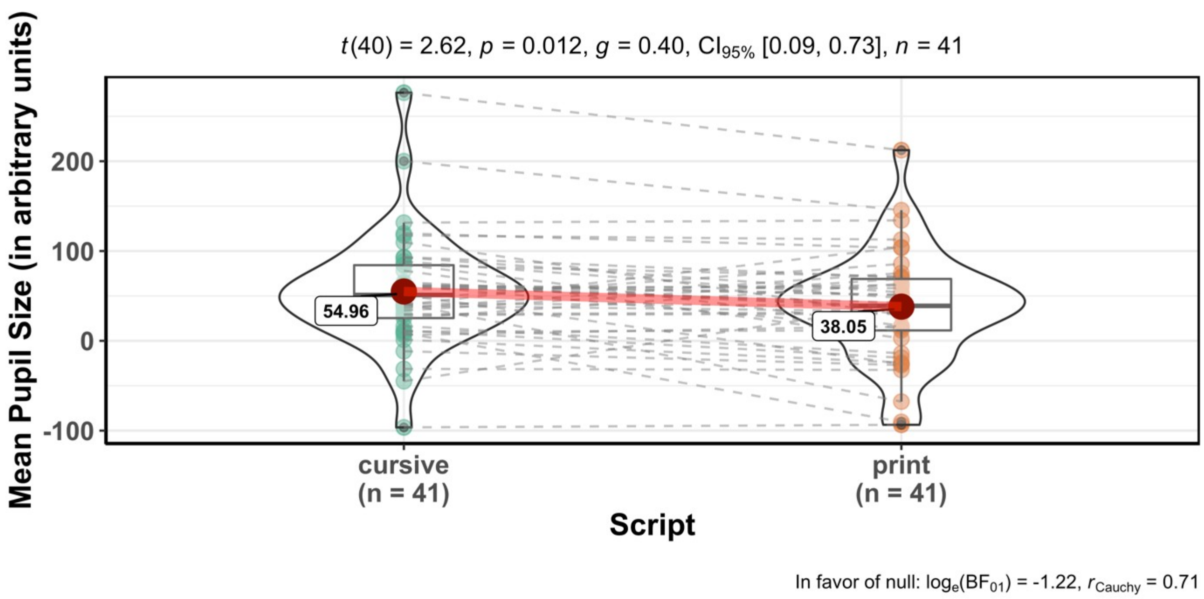


Figure 7. Mean Pupil Size.

```
#plot max pupil size

 mean<-ggstatsplot::ggwithinstats(
  data = mean_pup,
```

```
x = script,
y = maxpup,
title = "Mean Pupil Size",
xlab  = “Script”,            # turn off the default subtitle
Ylab = ="Mean Change in Pupil Size (arbituary units)”,
)
```

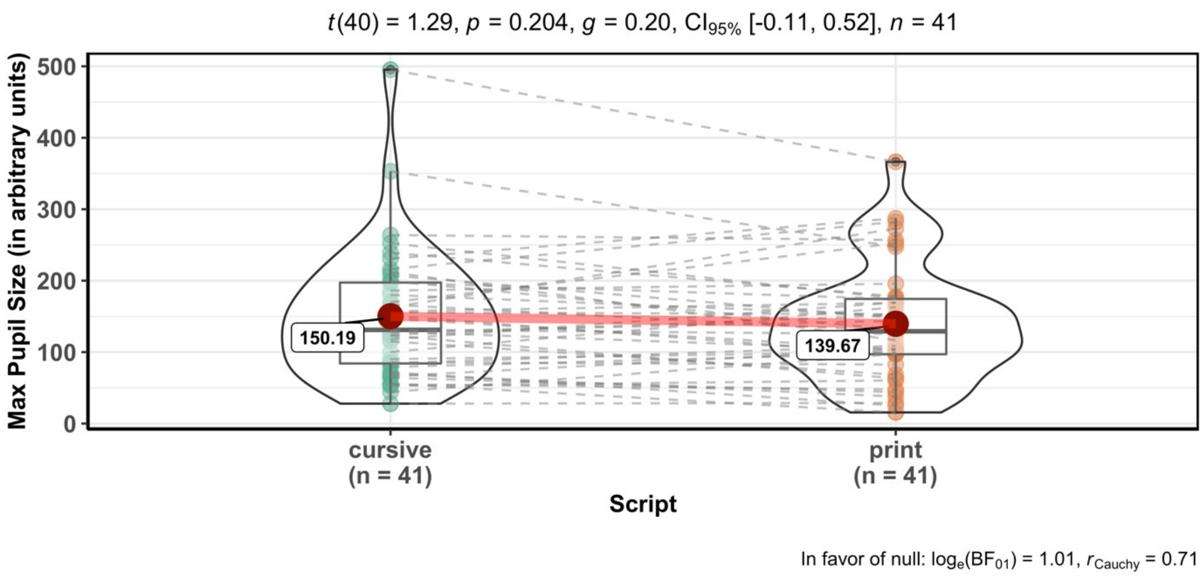


Figure 8. Max Pupil Size

Discussion

While there are a number of viable solutions available to process eye-tracking data, they are typically unsuitable for research for several reasons:

- An all-graphical interface seldom provides information about the underlying data analysis
- File formats are sometimes proprietary and undocumented, lacking detailed annotation necessary for replicability
- Source code and description of the algorithms are not accessible to the user
- Some implementations are expensive or rely on expensive underlying software.

The research community needs solutions that are completely open, with the possibility of directly manipulating and annotating the code, data, and parameters so that others may replicate or critique the methods. This article summarized and demonstrated the functionality of gazeR -- a free, open-source package written in R. We walked through important functions needed to pre-process your data and make it suitable for analysis. This provides a generalized, replicable, and transparent method for preprocessing raw eye-tracking data.

Limitations

There are several limitations of this package. The gazeR package is deliberately agnostic to type of statistical analysis. While the gazeR package does contain helper functions such as `code_poly` to facilitate growth curve analysis (GCA) using orthogonal polynomials (Mirman, 2014), the pre-processed results could also be analyzed using other functional forms (e.g., reverse Gaussian and logistic; Seedorff, Oleson, and McMurray, 2018) and/or statistical techniques (e.g., general additive models and functional data analysis; Jackson & Sirois, 2009). In the absence of a field-standard statistical approach, we leave it up to the researcher to choose what statistical analysis to use.

Another limitation is that the gazeR pre-possessing pipeline is not exhaustive. We included a set of functions that we think will suffice for researchers to pre-process their gaze and pupil data, but there are factors that are not included yet. For example, gaze position is known to influence pupil size (Brisson et al., 2013; Gagl, Hawelka, & Hutzler, 2011), called the pupil foreshortening effect. This effect occurs when rotations of the eyes change the angle at which the camera records the pupil, and therefore also the pupil's apparent size. As such, this manifestation of gaze position in pupil size should ideally be controlled or corrected for. A simple way to do this would be to include X and Y gaze coordinates into the analysis model as a co-variate.

Additionally, various aspects of pupil dilation might be more or less important to the analysis, which might benefit from examination of additional features such as onset and offset slopes (c.f., Winn & Moore, 2018). Because the gazeR package is open-source, modifications can always be made to incorporate additional functionality. Suggestions and contributions from users are encouraged and can be submitted through the package github page: https://github.com/dmirman/gazer.

Finally, the current instantiation of gazeR is limited to data that comes from the SR EyeLink. Much of the gazeR functionality is easily portable to data from other eye-trackers with the addition of functions for reading data and possibly renaming columns (variables) to match the EyeLink conventions.

To summarize, the gazeR package provides general, open-source tools for replicable and transparent processing gaze and pupillometry data. GazeR grew out of in-house preprocessing code in several research groups and is already being used by several additional research groups. It is our hope that more researchers will use it and will contribute to its improvement.

References

Attard-Johnson, J., Ó Ciardha, C., & Bindemann, M. (2019). Comparing methods for the analysis of pupillary response. *Behavior Research Methods*, *51*(1), 83–95. https://doi.org/10.3758/s13428-018-1108-6

Barnhart, A. S., & Goldinger, S. D. (2010). Interpreting chicken-scratch: Lexical access for handwritten words. *Journal of Experimental Psychology: Human Perception and Performance*, *36*(4), 906–923. https://doi.org/10.1037/a0019258

Beatty, J. (1982a). Task-evoked pupillary responses, processing load, and the structure of processing resources. *Psychological Bulletin*, *91*(2), 276–292. https://doi.org/10.1037/0033-2909.91.2.276

Bradley, M. M., Miccoli, L., Escrig, M. A., & Lang, P. J. (2008). The pupil as a measure of emotional arousal and autonomic activation. *Psychophysiology*, *45*(4), 602–607. https://doi.org/10.1111/j.1469-8986.2008.00654.x

Brisson, J., Mainville, M., Mailloux, D., Beaulieu, C., Serres, J., & Sirois, S. (2013). Pupil diameter measurement errors as a function of gaze direction in corneal reflection eyetrackers. *Behavior Research Methods*, *45*(4), 1322–1331. https://doi.org/10.3758/s13428-013-0327-0

Cohen, N., Moyal, N., & Henik, A. (2015). Executive control suppresses pupillary responses to aversive stimuli. *Biological Psychology*, *112*, 1–11. https://doi.org/10.1016/j.biopsycho.2015.09.006

Cooper, R. M. (1974). The control of eye fixation by the meaning of spoken language: A new methodology for the real-time investigation of speech perception, memory, and language processing. *Cognitive Psychology*, *6*(1), 84–107. https://doi.org/10.1016/0010-0285(74)90005-X

Einhauser, W., Stout, J., Koch, C., & Carter, O. (2008). Pupil dilation reflects perceptual selection and predicts subsequent stability in perceptual rivalry. *Proceedings of the National Academy of Sciences*, *105*(5), 1704–1709. https://doi.org/10.1073/pnas.0707727105

Forbes, S.H. (2019). pupillometryR: An R package for preparing and analysing pupillometry data. Retrieved from https://github.com/samhforbes/PupillometryR

Gagl, B., Hawelka, S., & Hutzler, F. (2011). Systematic influence of gaze position on pupil size measurement: analysis and correction. *Behavior Research Methods*, *43*(4), 1171–1181. https://doi.org/10.3758/s13428-011-0109-5

Geller, J., Landrigan, J.-F., & Mirman, D. (2019). A Pupillometric Examination of Cognitive Control in Taxonomic and Thematic Semantic Memory. *Journal of Cognition*, *2*(1). https://doi.org/10.5334/joc.56

Geller, J., Still, M. L., Dark, V. J., & Carpenter, S. K. (2018). Would disfluency by any other name still be disfluent? Examining the disfluency effect with cursive handwriting. *Memory & Cognition*, *46*(7), 1109–1126. https://doi.org/10.3758/s13421-018-0824-6

Geller, J., Still, M. L., & Morris, A. L. (2016). Eyes wide open: Pupil size as a proxy for inhibition in the masked-priming paradigm. *Memory & Cognition*, *44*(4), 554–564. https://doi.org/10.3758/s13421-015-0577-4

Goldinger, S. D., He, Y., & Papesh, M. H. (2009). Deficits in cross-race face learning: Insights from eye movements and pupillometry. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*(5), 1105–1122. https://doi.org/10.1037/a0016548

Grange, J.A. (2015). trimr: An implementation of common response time trimming methods. R package version 1.0.1. https://cran.r-project.org/web/packages/trimr/index.html

Granholm, E., Asarnow, R. F., Sarkin, A. J., & Dykes, K. L. (1996). Pupillary responses index cognitive resource limitations. *Psychophysiology*, *33*(4), 457–461. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8753946

Hershman, R., Henik, A., & Cohen, N. (2018). A novel blink detection method based on pupillometry noise. *Behavior Research Methods*, *50*(1), 107–114. https://doi.org/10.3758/s13428-017-1008-1

Karatekin, C., Couperus, J. W., & Marcus, D. J. (2004). Attention allocation in the dual-task paradigm as measured through behavioral and psychophysiological responses. *Psychophysiology*, *41*(2), 175–185. https://doi.org/10.1111/j.1469-8986.2004.00147.x

Kret, M. E., & Sjak-Shie, E. E. (2018). Preprocessing pupil size data: Guidelines and code. *Behavior Research Methods*, 1–7. https://doi.org/10.3758/s13428-018-1075-y

Mathôt, S. (2018). Pupillometry: Psychology, Physiology, and Function. *Journal of Cognition*, *1*(1). https://doi.org/10.5334/joc.18

Mathôt, S., Fabius, J., Van Heusden, E., & Van der Stigchel, S. (2018). Safe and sensible preprocessing and baseline correction of pupil-size data. *Behavior Research Methods*, *50*(1), 94–106. https://doi.org/10.3758/s13428-017-1007-2

Murphy, P. R., O'connell, R. G., O'sullivan, M., Robertson, I. H., & Balsters, J. H. (2014). Pupil diameter covaries with BOLD activity in human locus coeruleus. *Human Brain Mapping*, *35*(8), 4140-4154.

Nyström, M., Hooge, I., & Andersson, R. (2016). Pupil size influences the eye-tracker signal during saccades. *Vision Research*, *121*, 95–103. https://doi.org/10.1016/J.VISRES.2016.01.009

Patil, I. (2018). ggstatsplot:“ggplot2” Based Plots with Statistical Details. CRAN.

Piquado, T., Isaacowitz, D., & Wingfield, A. (2010). Pupillometry as a measure of cognitive effort in younger and older adults. *Psychophysiology*, *47*(3), 560–569. https://doi.org/10.1111/j.1469-8986.2009.00947.x

Reilly, J., Kelly, A., Kim, S. H., Jett, S., & Zuckerman, B. (2018). The human task-evoked pupillary response function is linear: Implications for baseline response scaling in pupillometry. *Behavior Research Methods*. https://doi.org/10.3758/s13428-018-1134-4

Salverda, A. P., & Tanenhaus, M. K. (2018). The visual world paradigm. In Annette M. B. de Groot and Peter Hagoort (Eds) *Research methods in psycholinguistics and the neurobiology of language: A practical guide*, pp. 89-110. Wiley Blackwell.

Satterthwaite, T. D., Green, L., Myerson, J., Parker, J., Ramaratnam, M., & Buckner, R. L. (2007). Dissociable but inter-related systems of cognitive control and reward during decision making: Evidence from pupillometry and event-related fMRI. *NeuroImage*, *37*(3), 1017–1031. https://doi.org/10.1016/j.neuroimage.2007.04.066

Seedorff, M., Oleson, J., & McMurray, B. (2018). Detecting when timeseries differ: Using the Bootstrapped Differences of Timeseries (BDOTS) to analyze Visual World Paradigm data (and more). *Journal of Memory and Language*, *102*, 55–67. https://doi.org/10.1016/J.JML.2018.05.004

Siegle, G. J., Steinhauer, S. R., Carter, C. S., Ramel, W., & Thase, M. E. (2003). Do the Seconds Turn Into Hours? Relationships between Sustained Pupil Dilation in Response to Emotional Information and Self-Reported Rumination. *Cognitive Therapy and Research*, *27*(3), 365–382. https://doi.org/10.1023/A:1023974602357

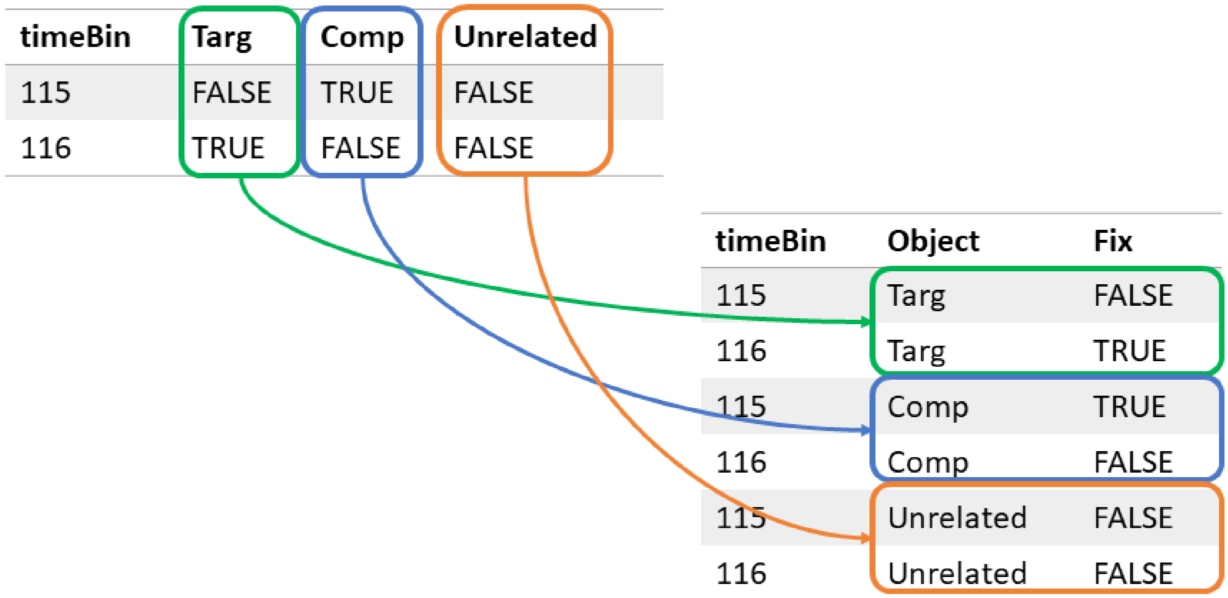
Tanenhaus, M. K., Spivey-Knowlton, M. J., Eberhard, K. M., & Sedivy, J. C. (1995). Integration of visual and linguistic information in spoken language comprehension. *Science (New York, N.Y.)*, *268*(5217), 1632–1634. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/7777863

Tsukahara, J.S. (2018). pupillometry: An R Package to Preprocess Pupil Data. Retrieved from https://dr-jt.github.io/pupillometry

Van Gerven, P. W. M., Paas, F., Van Merriënboer, J. J. G., & Schmidt, H. G. (2004). Memory load and the cognitive pupillary response in aging. *Psychophysiology*, *41*(2), 167–174. https://doi.org/10.1111/j.1469-8986.2003.00148.x

Winn, M. B., Wendt, D., Koelewijn, T., & Kuchinsky, S. E. (2018). Best Practices and Advice for Using Pupillometry to Measure Listening Effort: An Introduction for Those Who Want to Get Started. *Trends in Hearing*, *22*, 2331216518800869. https://doi.org/10.1177/2331216518800869

Supplemental Figure: A demonstration of how tidyr::gather converts “wide” data with three separate object columns into “long” data that contains a “key” variable (Object) and a “value” variable (Fix).


timeBin
Targ
Comp
Unrelated
115
FALSE
TRUE
FALSE
116
TRUE
FALSE
FALSE
timeBin
Object
Fix
115
Targ
FALSE
116
Targ
TRUE
115
Comp
TRUE
116
Comp
FALSE
115
Unrelated
FALSE
116
Unrelated
FALSE