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Project Report: Pupillary light reflex

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Introduction to Computational Neuroscience (MTAT.03.291)
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Contents

Introduction	2
Data collection	3
Data preprocessing	4
Hypothesis testing	9
Machine learning	12
Conclusion	15
References	16

Introduction

The main idea of the project is to test the next hypothesis: is that true that if the brain

knows that it will soon see dark or bright objects it starts changing and adopting the pupil size before object occurs.

The whole project divides into next steps:

- 1. Data collection
- 2. Data preprocessing
- 3. Hypothesis testing
- 4. Machine learning

Data collection

Data collection was the first part of the research. During this stage the

condition of the experiment has been changed, after the first collections have been done. There were proposed several improvements of the experiment, that highly probable would gave the better results.

Initially, the data collection flow consists of 2 experiments:

- 1. Subjects will be adjusted to the complete darkness for 2 min, after which background color of the screen will turn briefly white. Altogether 5 trials of PLR will be measured (with ITI of 30 s). After that the 3 main parameters were calculated: Diameter, Velocity and Acceleration.
- 2. In this task the background color keeps changing from gray to black or white. Participants task is to indicate as quickly as possible whether the background turned into black or white. If the background turns white participant presses the right and if it turns black left arrow key (there are markings on the keyboard). Before the background changes the participant will be presented either a combination of numbers that are always related to the same color or combination of numbers that are not meaningfully related to the color.

After the first collection (form 5 subjects) the condition of the experiments have been changed:

- Changed the pointers
- Changed stimulus timings
- Proposed a fake motivation based on (best result (50 100))

Totally, there the data was collected approximately from 30 participants, (currently working with the data from 27 participants).

Data preprocessing

After some data investigation we figured out how is converted ASCII data structured. The lines which begins with '**' are comments, we can ignore them.

'MSG {timestamp} ' -- messages from eyelink, some of them, like calibration, validation, various hardware settings we can omit, but some of them contain events of cue or stimulus. Possible cue values are 'right', 'left', or 'rndCue', which were shown to the participants as 132, 231 and 182/281 respectively. Possible stimulus -- 'right' and 'left', which historically means black screen color and white.

Here is an example of one such message: 'MSG 12031772 right'. Starting of each trial marked with line like this: 'START {timestamp} RIGHT SAMPLES EVENTS', and end marked similarly with this: 'END {timestamp} SAMPLES EVENTS RES 26.79 27.82'. Main data content contains following lines: '12041268 477.2 383.1 1912.0 ...'. Each line contains timestamp, participant gaze coordinates and relative pupil size.

For processing data we need to load it, therefore couple of data structures were written for storing trials, and parser for loading this data into memory. For this purpose regular we used mainly regular expressions. Loaded data contains a lot of blinks, which should be handled.

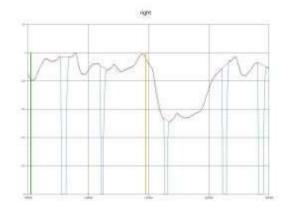
The main algorithm for detecting them is based on the diameter changing speed. Pupil cannot change its size too fast, therefore places, when speed is too high (higher than some set threshold) can be interpreted as eye in process of closing/open. The regions with no data usually mean, that the eye is closed.

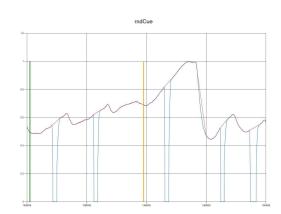
For removing blinks following steps were applied:

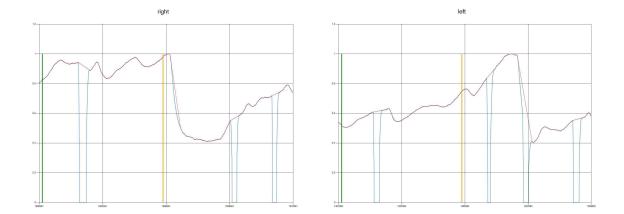
1. Check start of the recording. If person was in process of blinking during the beginning of the recording, we cannot interpolate the data, and therefore we put in this place first valid value (not the first, but close to it, as pupil need some time to adjust after the blackness during the blink. This time is adjustable).

- 2. Check the end of the recording. Same as before, but from the end. If recording ends with blink, for those empty values we put last valid data.
- 3. Find the regions, where pupil's size changes too rapidly, and mark them as abnormal.
- 4. Find and mark the regions, where data lasts too shortly (e.g. 10 ms of data inside of second of emptiness)
- 5. Extend marked regions to cover edges, where data can be not 'stable' (slow beginning of blink, adjusting after blink, etc.)
- 6. Interpolate values in unmarked areas -- we used linear interpolation, which means that we connected beginning of marked region and its end with the straight line.
- 7. After blinks interpolation we plotted the data to evaluate the result and adjust all the defined constants.

Here is some of the results we've got:



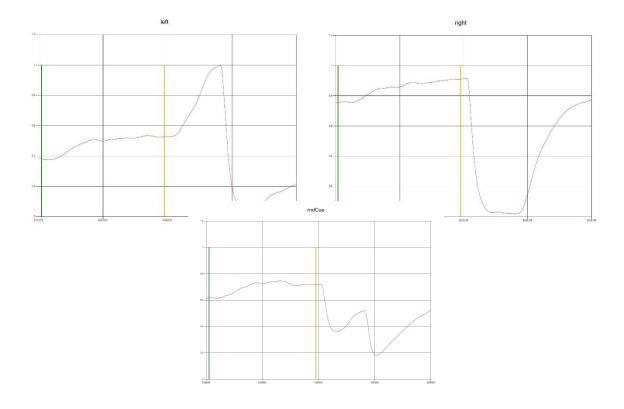




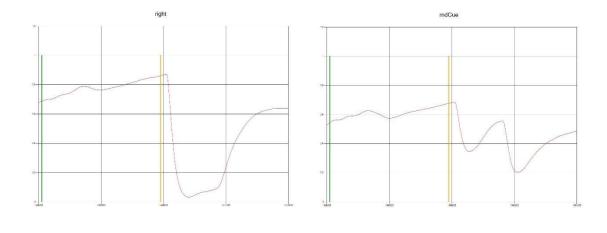
Blue curve -- raw data, curve -- interpolated, green line -- cue, Yellow -- stimulus, header shows type of stimulus. On the X axis time, on Y -- diameter.

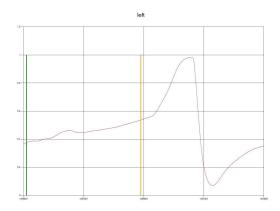
For the interpolated blink data we have performed normalization -- minimum and maximum diameter was taken as zero and one, and all the values in between were interpolated.

For all the people we have plotted average values of the diameter for all types of stimulus (three graphs for each person).



Also, the same graphs were created for all the trials.





One thing we tried -- compare pupil size right before showing a cue, and before changing a color. For the "right" cue (followed by white color) this difference should be less than for "left". The actual result is that in average for 16 people this hypothesis confirmed, but for 11 not. Also, this difference varies a lot from almost zero, therefore we cannot think that this part confirms anything.

Hypothesis testing

<u>Hypothesis:</u> Size of the pupil will decrease during the time before cue in "white" and increase in "black" trials compared to control (random) condition.

Let X, Y, Z – are the random variables of the size of the pupil of a particular participant after the white cue, black cue and random cue.

Let M_x , M_y , M_z are the means of the diameter of a pupil of a particular participant after the combination of cues for white, black and random screen presented, in turn.

Mathematically, we will test the following hypothesis:

1.
$$H_0: M_x = M_z$$

$$H_1: M_x \neq M_z$$

We anticipate that the mean diameter of a pupil when the participant knows that the color of the screen will be white is different from the case the participant has a random cue and can't know the color of the screen in the next moment.

2.
$$H_0: M_v = M_z$$

$$H_1: M_{\nu} \neq M_z$$

We anticipate that the mean diameter of a pupil when the participant knows that the color of the screen will be black is different from the case the participant has a random cue and can't know the color of the screen in the next moment.

3.
$$H_0: M_x = M_y$$

$$H_1: M_x > M_y$$

We anticipate that the mean diameter of a pupil when the participant knows that the color of the screen will be black is bigger, than in case the participant knows that the color of the screen will be white.

To test the hypothesis above we firstly should test hypothesis about variance equality.

Let
$$D_x$$
, D_y , D_z – be the variances for X, Y, Z respectively.

Because we don't know if variances of X, Y, Z are equal, we firstly should check the following hypothesis:

1.
$$H_0: D_x = D_z$$

2.
$$H_0: D_y = D_z$$

3.
$$H_0: D_x = D_y$$

Null hypothesis $H_0: \frac{\sigma^2 \chi}{\sigma^2 \gamma} = 1$,	Test statistics: $F_{obs} = \frac{s^2 x}{s^2 y}$
Alternative hypothesis H_1 :	Rejection region:
$\frac{\sigma^2_X}{\sigma^2_Y} \neq 1$	$F_{obs} \ge F_{\frac{\alpha}{2}}(n-1, m-1)$

After we check the hypothesis about the variance, there are two possible outcomes:

Hypothesis H_0	Conditions	Test statistic	Degrees of freedom
$\mu_X = \mu_Y$	Sample sizes n, m; unknown but equal standard deviations,	$t = \frac{\bar{X} - \bar{Y}}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}}$	n + m - 2
	$\sigma_X = \sigma_Y$		
$\mu_X = \mu_Y$	Sample sizes n, m; unknown, unequal standard deviations,	$t = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{s^2 X}{n} + \frac{s^2 Y}{m}}}$	Satterthwaite approximation
	$\sigma_X \neq \sigma_Y$		

where:

$$s_p^2$$
 – pooled sample variance

$$s_X^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

For each participant for each trial we calculated mean pupil size. Therefore, for each participant we had 3 samples (because of 20 trials each sample of length 20) of mean pupil size after the cue in trials for black, white and random. Then we tested hypothesis based on theory above. We tested above mentioned hypothesis with 5% level of significance.

The results of the hypothesis testing are the following: for all participants all three hypotheses were accepted. This means that mean pupil sizes after white, black and random cue are equal.

Machine learning

Predicting which color was shown based on reaction after it.

For the first model we decided to predict which color was shown: black or white, based on features which are: pupil diameters in 1.8 second for every person and for every trial of person. In total, we had 1326 observation and 900 variables.

We excepted to predict with accuracy more than 95% since you can obviously say looking at data which color was shown.

Machine learning part was done using R language and RStudio environment, since it is the most confident and simple way to solve machine learning tasks

The first step was splitting data to testing and training set, with training sample size being 75% of all dataset and testing 25%.

We had to choose the most optimal method for learning model, which would perform well with classification problem and get good results in reasonable time, so we stopped with Random forest.

Random forest (or decision forest) is ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes.

The algorithm of Random forest is following:

- 1. Draw **n** bootstrap samples from the original data (in our case number of trees(n) is 500)
- 2. For each of the bootstrap samples, grow an unpruned classification tree with the following modification: at each node rather than choosing the best split among all predictors, try random sample of predictors and choose the best split among those variables.
- 3. Predict new data by aggregating the predictions of the trees (i.e., majority votes for classification, average for regression).

An estimate of the error rate can be obtained, based on the training data, by the following:

- 1. At each bootstrap iteration, predict the data not in the bootstrap sample (what Breiman calls "out-of-bag", or OOB, data) using the tree grown with the bootstrap sample.
- 2. Aggregate the OOB predictions. (On the average, each data point would be out-of-bag around 36% of the times, so aggregate these predictions.) Calculate the error rate, and call it the OOB estimate of error rate.

After learning model on training set we got following confusion matrix:

```
black white class.error
black 493 3 0.006048387
white 2 496 0.004016064
```

When we tried model on testing data set we got 371 out of 372 values predicted right. So model have pretty good accuracy, and we can conclude that it is really easy to spot which color was shown to person based on its reaction on it.

Predicting what was shown after color changing based on reaction before stimulus

Even though our hypothesis failed, we tried to build main prediction model and see how accurate it is.

Given following predictors: pupil diameters in 3.8 second for every person and for every trial of person. In total, we had 1326 observation and 1950 variables. We predict whether 'left', 'right' or 'random' number was shown. Left corresponds to black color, right for white.

We did the same manipulation on data as described below and also use Random forest model in order to predict values.

After learning model on training set we got following confusion matrix:

```
left right rndCue class.error
left
        105
              120
                     100
                           0.6769231
right
        115
              117
                     107
                           0.6548673
rndCue
        115
              104
                     111
                           0.6636364
```

And after checking it on test data set we got 33% predicted right. So the conclusion is pretty obvious this model predict really randomly (33% is the chance to pick correct from 3 randomly) and we again can say that it is impossible to predict which number was shown to participant based on reaction before it.

Conclusion

During the project there were 27 participants. The main idea was tested from both theoretical and practical way. Both of these approaches shown that the hypothesis is not valid and this means that pupil doesn't adopt before appearing dark or bright object.

The first problems appeared during colleting the data stage. We successfully fixed them by adding new features to the experiment conditions. After that we collected the data and clean it, successfully interpolate blinks and delete outliers. Then we tested statistical hypotheses about the equality of two sample means and applied machine learning to verify our results.

References

Fotiou, D. F., Brozou, C. G., Haidich, A.-B., Tsiptsios, D., Nakou, M., Kabitsi, A., Fotiou, F (2007). Pupil reaction to light in Alzheimer's disease: evaluation of pupil size changes and mobility. Aging Clinical and Experimental Research, 19(5), 364–371.