Predicting licking during a visual change detection task

Alex Piet, Nick Ponvert, Ildefons Magrans de Abril, Kate Roll

Our proposal seeks to quantify mouse behavior during the visual change detection task on a moment-by-moment basis. Quantification of behavior may reveal interesting lines of investigation into the neural coding underlying behavior. The goal for this project would be to build a generalized linear model (GLM) to predict licking events for each mouse. The motivation for modeling licking is to 1) quantify the impact of various external or measured variables on the mouse's behavior, and 2) to quantify the mouse's behavioral state. We propose to model licks as poisson events generated by a time-varying latent rate, which is estimated by a sum of external variables.

$$\text{licks} \approx Poisson\left(\lambda(t)\right) \tag{1}$$

$$\lambda(t) = \sum_i f_i\left(x_i(t)\right). \tag{2}$$

GLMs have been used extensively in neuroscience to model neural spikes trains [3]. GLMs have also been used readily to model behavioral responses, and have revealed interesting neural mechanisms [1, 2]. Here, each $x_i(t)$ is the time course of a measured variable, for example running speed, image presentation or image identity, lick history, cumulative water reward, individual water rewards, time in session, pupil diameter, eye position, facial features extracted from behavioral video, etc. Each $f_i\left(x_i(t)\right)$ is a weighting function that maps each measured variable onto a scalar value. Exploring the exact form of $x(t)$ and $f(x)$ would be a major part of this project. Each function $f(x)$ can be parameterized based on the specific form expected from the specific $x(t)$. For example, we expect licking to stop when the mouse is running, so an appropriate transfer function would be a sigmoid that maps low running to high licking probability, and high running to low licking probability. We will fit this model by maximum likelihood estimation, finding the parameter weights that maximize the probability of observing the pattern of licks displayed by each mouse. After the model has been fit, the latent variable $\lambda(t)$ is a prediction of the mouse's moment-by-moment licking probability.

1. Specific Steps and Stretch Goals

Establishing a simple model using only one external variable $x(t)$ will be relatively simple. We can then proceed by iteratively adding more external variables and quantifying how well each additional variable improves the fit. Rigorous model validation methods like cross-validation and Bayesian Information Criterion comparisons can take place as well.

Depending on time, or perhaps after Thursday Harbor, there are a number of possible extensions. As one example, we could use hierarchical models to better fit the entire population. This is conceptually straightforward, but might involve some coding effort. Proper hierarchical models will take advantage of the standardized behavior across many mice on this task. This is a unique opportunity with this dataset, as most behavioral studies are under powered, and have variable conditions for each subject.

2. Value for the broader Visual Behavior Project

This project promises to have benefit to the larger Visual Behavior project, and takes advantage of key features of this dataset.

- During the SAC meeting, several members commented on the need to incorporate behavioral data like pupil diameter, and face videos. During a recent Visual Behavior meeting, there was a growing consensus that we need more behavioral analysis.

- This task has standardized behavior with many subjects, this is a unique dataset, and this project is a step towards utilizing the power of that standardized behavior.

- This project will quantify subject-to-subject variability at the behavioral level, which could help explain variability at the neural level.

- The learned weighting functions $f(x)$ give us a list of potentially important features to examine in the neural code. For example, the learned function that maps reward history onto licking probability might have temporal structure that reflects the mouse's understanding of the timing of the task. This would manifest as a function that has lower licking probability at the start of each trial. For a preliminary example, see Figure 1. Quantifying this timing signal could help understand neural dynamics.

- The latent variable $\lambda(t)$ gives us a time-varying continuous variable that can be used in neural analysis. For example, if a combination of factors estimate a mouse is disengaging during parts of a session, indicated by a low $\lambda(t)$, then the neural coding during that portion of a session could be analyzed separately from high $\lambda(t)$ epochs.

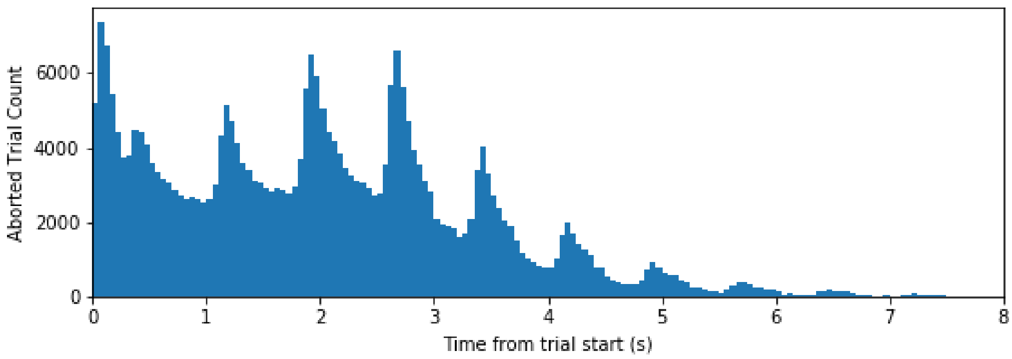

Figure 1: **Histogram of the time of first lick on aborted trials** The timing of aborted licks has temporal structure on multiple timescales reflecting both trial structure and image flash structure. Quantifying these patterns may reveal temporal signals in the neural data.

3. Summary

We propose to quantify mouse behavior during the visual change detection task, specifically predicting licking events with on a fine timescale. By quantifying what factors influence licking, we may gain insight into the behavioral strategies and states of the mice. This insight should translate into increased understanding of the neural dynamics recorded in the Visual Behavior pipeline. Our proposed model is conceptually straight-forward, has been used in the field, but has many interesting stretch goals. Finally, our proposed project can be segmented into chunks that an individual can easily work on. For example, each person can pick a different external variable $x(t)$, and transfer function $f(x)$. In this manner, the group can likely be very efficient and productive in a short time window like the Thursday Harbor retreat.

References

[1] Athena Akrami, Charles D. Kopec, Mathew E. Diamond, and Carlos D. Brody. Posterior parietal cortex represents sensory history and mediates its effects on behaviour. *Nature*, 554:368 EP –, Feb 2018.

[2] Kevin J. Miller, Matthew M. Botvinick, and Carlos D. Brody. Dorsal hippocampus contributes to model-based planning. *Nature Neuroscience*, 20:1269 EP –, Jul 2017. Article.

[3] Il Memming Park, Miriam L. R. Meister, Alexander C. Huk, and Jonathan W. Pillow. Encoding and decoding in parietal cortex during sensorimotor decision-making. *Nature Neuroscience*, 17:1395 EP –, Aug 2014. Article.