Big Neuro + Movement

Kevin Li, Tengjiao Liu, Yuyan Liu, Cara Tan, Yuchong Zhang

RICE

Baylor College of Medicine

1. Introduction

Background

Recent studies have shown that mice visual responses are strongly modulated by their movements. One study found that firing rates in vision-related neurons doubled when the mouse transitioned from still to running.

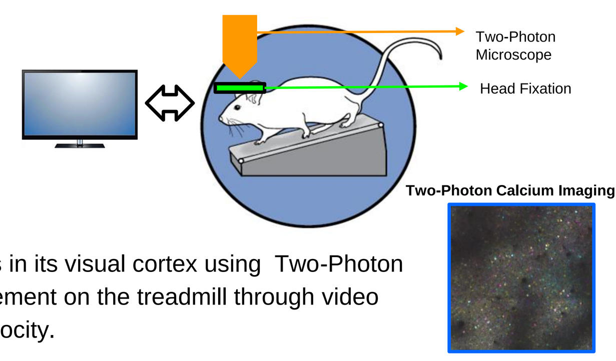
We want to continue these studies by focusing specifically on how cells in the visual cortex are correlated with mouse movement. Should we find positive correlations, our findings will show that non-visual context such as movement can influence even the most fundamental features of vision such as the visual cortex. This knowledge can contribute to our models of how the brain "sees".

Objectives

1. Quantify and extract movement from the videos.
2. Perform Neuronal Tuning on chosen body parts
3. Create models to predict different types of movement from visual cortex neuron firing rates
4. Make conclusions on whether correlation exists between visual responses and movement

Setup

For our setup, we have a mouse watching a monitor as shown in the figures to the right. The mouse head is fixed but it is free to run on the treadmill and respond to stimuli on the monitor.



To collect visual data, we measured neurons in its visual cortex using Two-Photon Calcium Imaging. We also recorded its movement on the treadmill through video as well as measurements of the treadmill velocity.

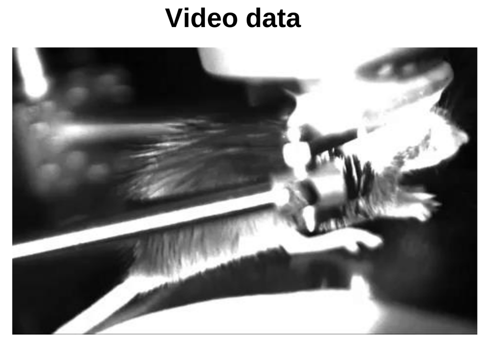
Data Description

For our experiment, we collected data on the following features across the timespan of approximately 2 hours:

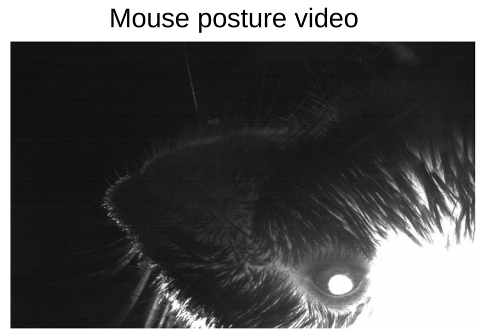
1. Two-Photon Calcium measures of 6333 neurons in 3 layers of the visual cortex
2. Video of mouse Pupil
3. Values of pupil radius and centroid (center of pupil) position throughout the video
4. Video footage of mouse on the treadmill
5. Treadmill velocity

2. Data Visualization

Video data

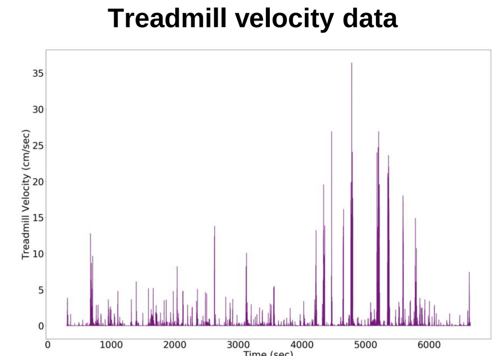


Mouse posture video



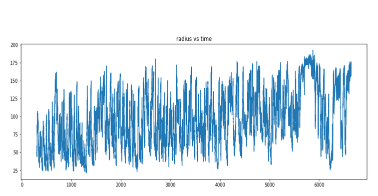
Mouse pupil video

Treadmill velocity data

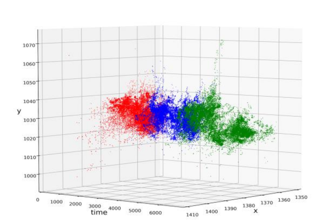


Treadmill velocity across time

Pupil data

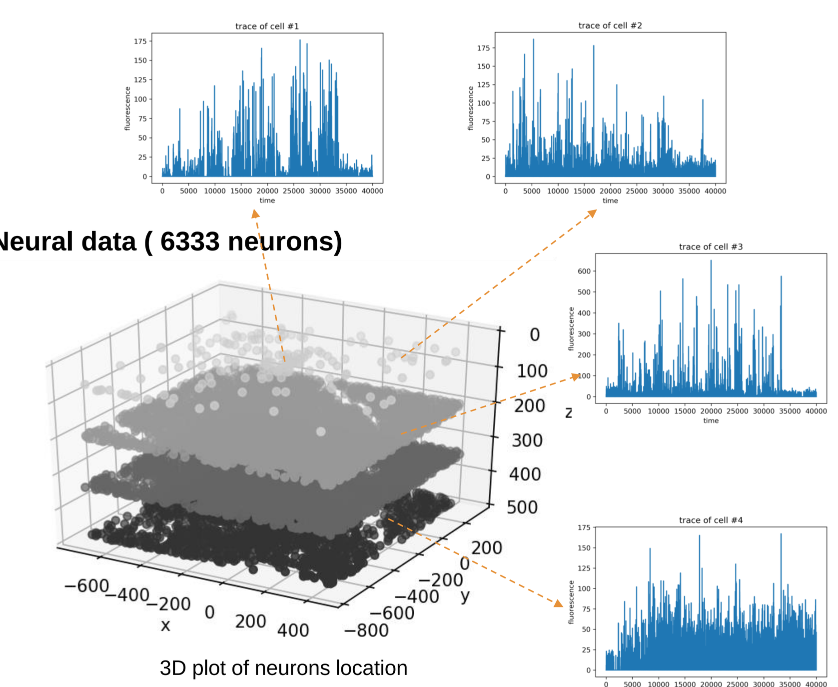


Pupil radius across time



Pupil centroid location across time

Neural data (6333 neurons)



3D plot of neurons location

3. Pipeline

- Balanced splitting
- Train/test ratio=85%/15%

Data Splitting

- Continuous
- Categorical

Extract Movement

- Univariate regression
- Lasso regression

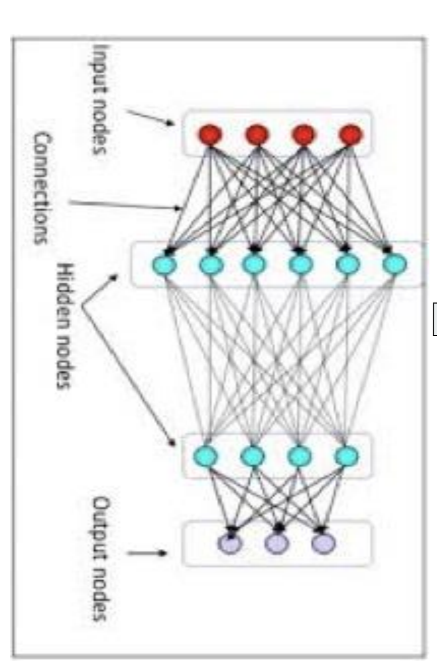
Neuronal Tuning

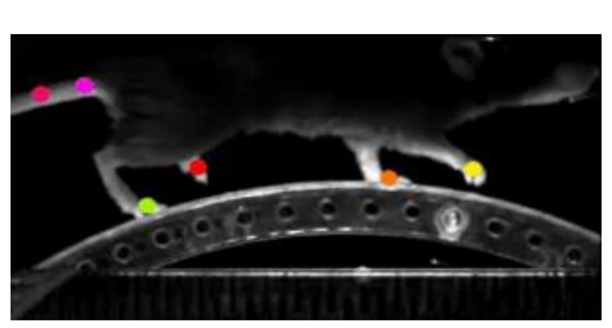
- Linear regression
- Logistic regression

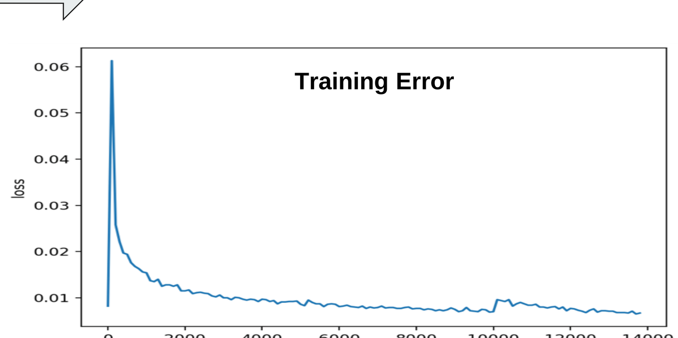
Predictive Model

4. Extraction of Mouse Movements

DeepLabCut





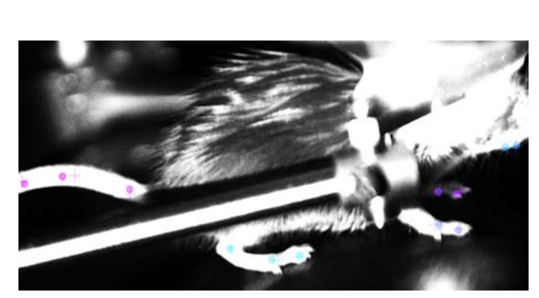


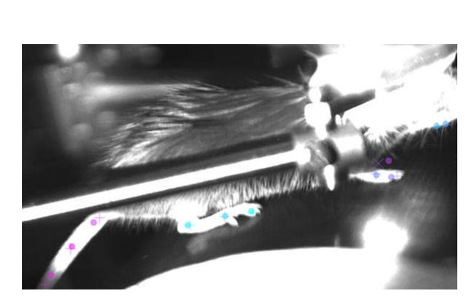
Train Model to Label Video

The video contained the majority of our movement data. Since the mouse's head is fixed, it is only able to move its tail, paws, jaw, and pupil. Therefore, we decided to divide the task of quantifying movement into these 4 categories. The positions of the jaw, paws, and tail are approximated using one or more coordinates representing critical points of movement on the body part, such as joints and areas of curvature. The image on the bottom demonstrate how we want to represent the body parts.

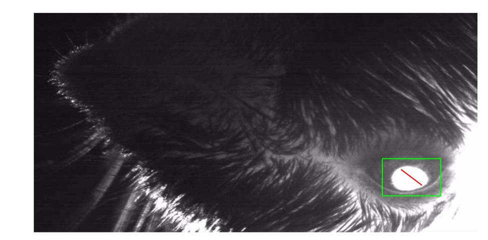
Since the video contains thousands of frames, it was impractical to hand label every frame. Therefore, we used a specialized neural network called DeepLabCut to automate this process. We hand-labeled several diverse frames of the video and then used those frames to train the neural network. The graph on the left shows the convergence of the model as it learned from the training set.

The model finished with a training and testing error of approximately 5 and 12 pixels, respectively. The error is quite small, and upon manual inspection, the model produced satisfactory results. Below shows an image taken from the testing set where the model predictions are crosses and the human labels are dots. The model predictions are quite close to the human labels, even accommodating for the hidden front paw on the right image, which it doesn't label.

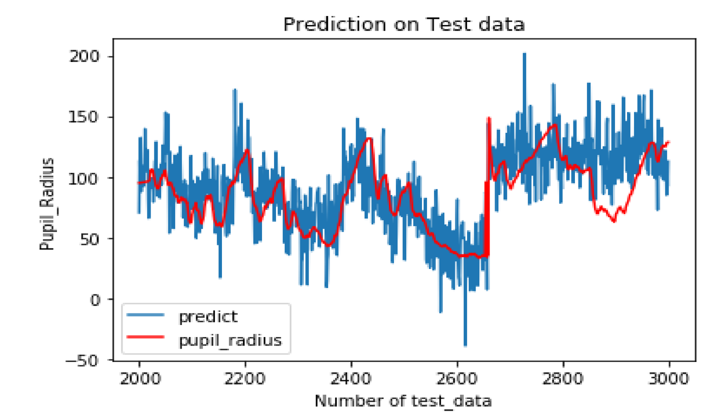




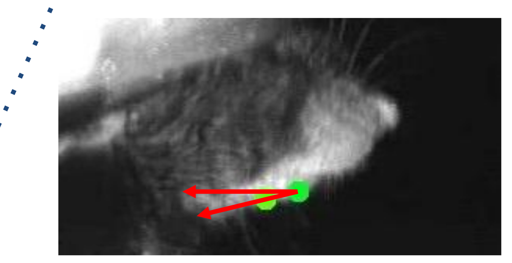
5. Modelling by Body Parts



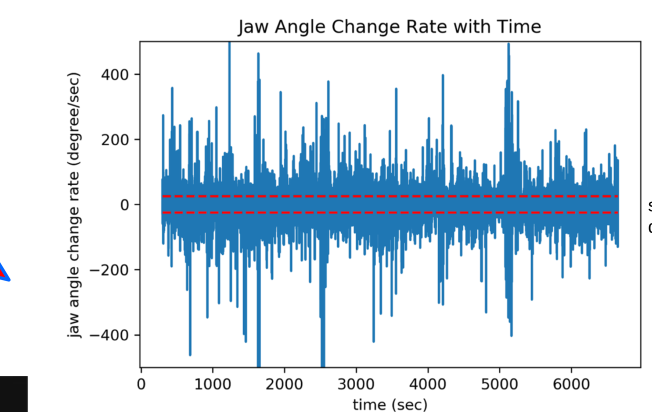
PUPIL



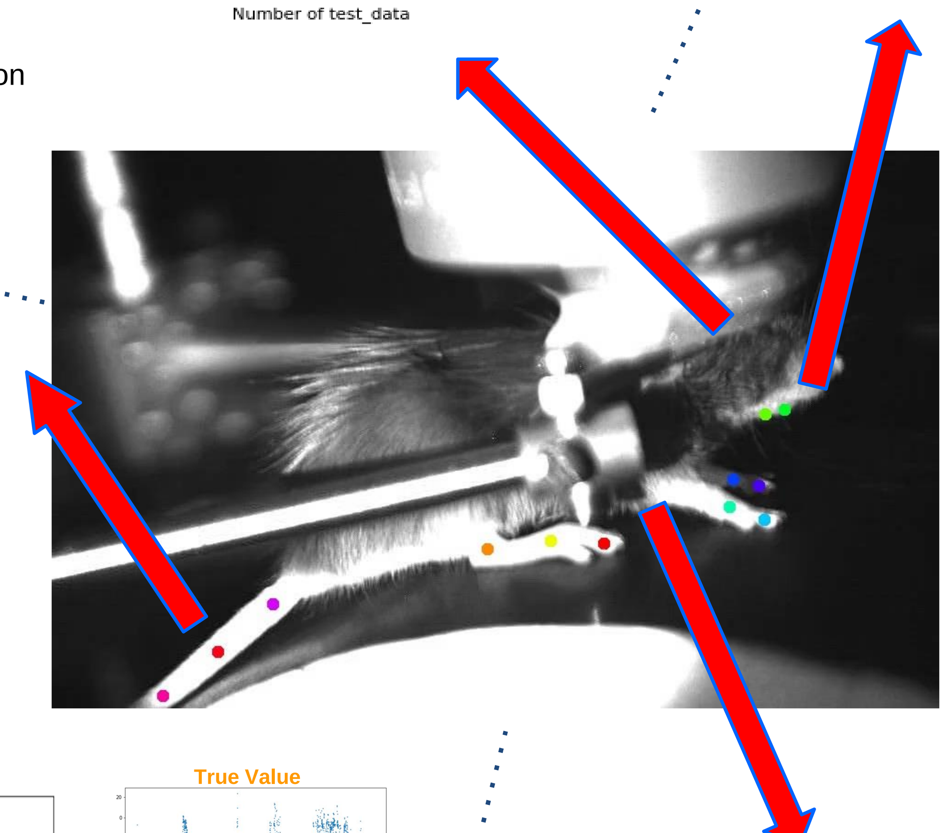
Value function: Pupil radius
Model: Multivariate Linear Regression
Selected Neurons: 4921 neurons
Adjusted R-squared: 0.884



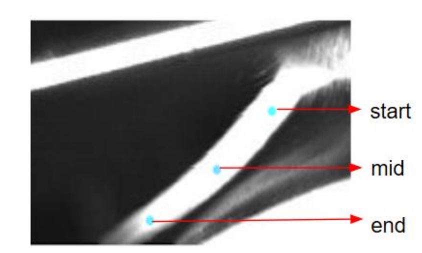
JAW



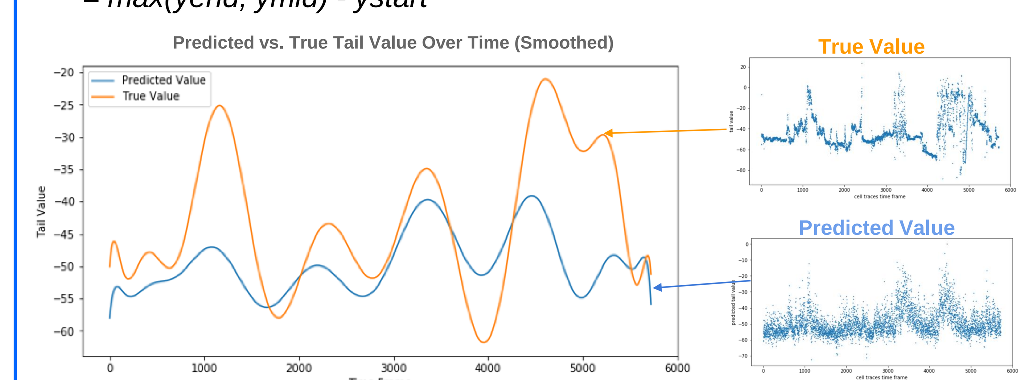
Value function: Jaw up/still/down
Model: Multinomial Logistic Regression with Lasso
Selected Neurons: 392 neurons
Test Accuracy: 37.2%



TAIL

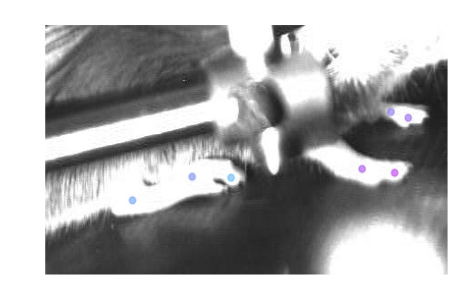


Value function
TailHeight(ystart, ymid, yend) = max(yend, ymid) - ystart

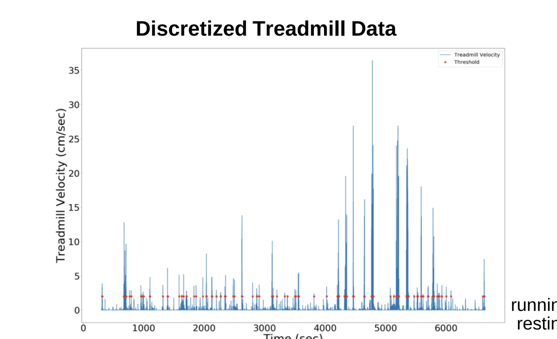


Univariate Selection: 506 neurons

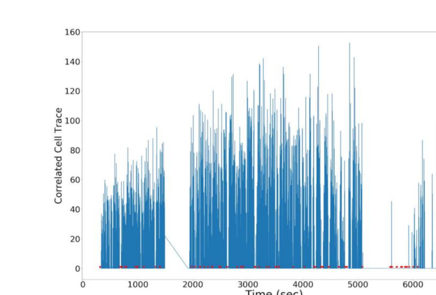
Model: Multivariate Linear Regression



PAWS

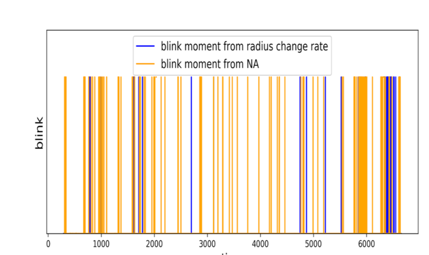


example of a neuron with a negative correlation



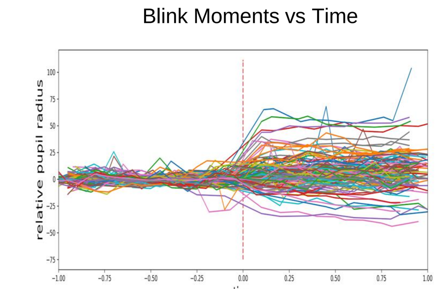
Value function: mouse running/resting
Model: LASSO Logistic Regression
Selected Neurons: 860 neurons
Test Accuracy: 94.7%

6. Blinking Effect



Blink Moments vs Time

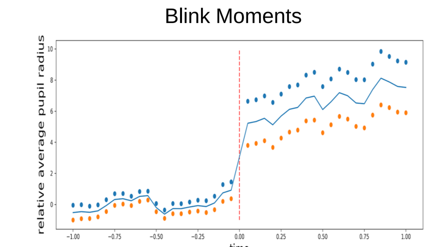
Blink moments are extracted from NAs and relatively large pupil radius change rate time points.



a. Relative Pupil Radius Before and After Blink Moments

x-axis: a two-second window around a blinking event.

y-axis: relative pupil radius, i.e. each radius data in the same blink period is subtracted the mean of pre-blink radius values.



b. Relative Average Pupil Radius Before and After Blink Moments

blue and yellow points in figure b: bounds of ± 1 standard deviation of pupil radius.

After each blink, pupil radius tends to become larger as well as less stable.

7. Summary

Body part	Movement type	# selected cells	Correlation
Jaw	raise/drop	392	no
Tail	height	506	poor
Paws	running/resting	860	some
Pupil	radius	4921	high

- ❑ Extracted movement features from videos and matrix datasets
- ❑ Explored the correlation between neuron activities and different movements
- ❑ Pupil movement is highly correlated with the neuron activities

8. Future Work

- ❑ Account for time lag
- ❑ Use movement combinations as predictors
- ❑ Experiment with other data science models (e.g. HMM)

Reference

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[7] Frederick Campbell, Genevera I Allen, et al. Within group variable selection through the exclusive lasso. Electronic Journal of Statistics, 11(2):4220-4257, 2017.