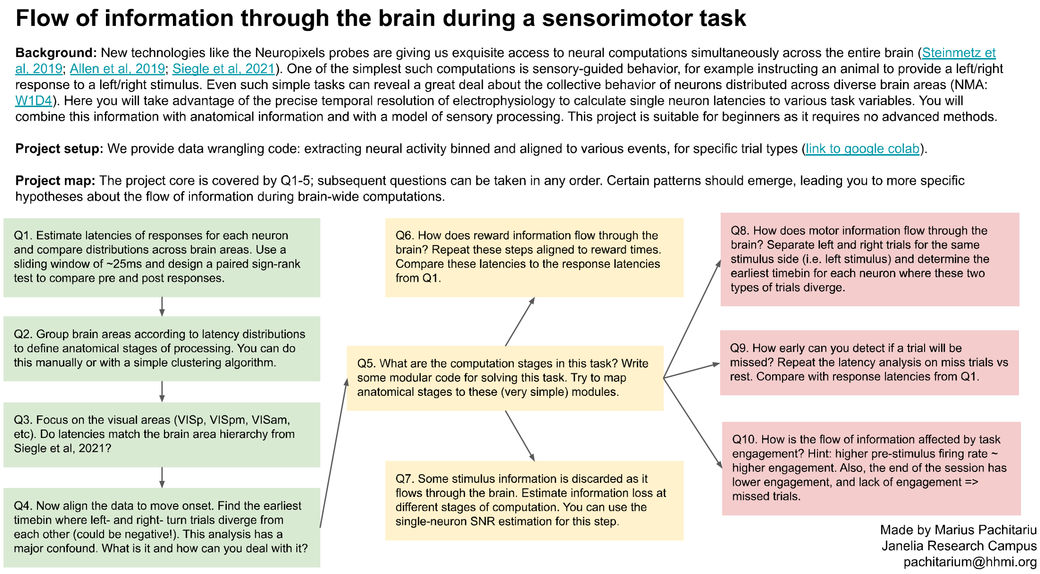
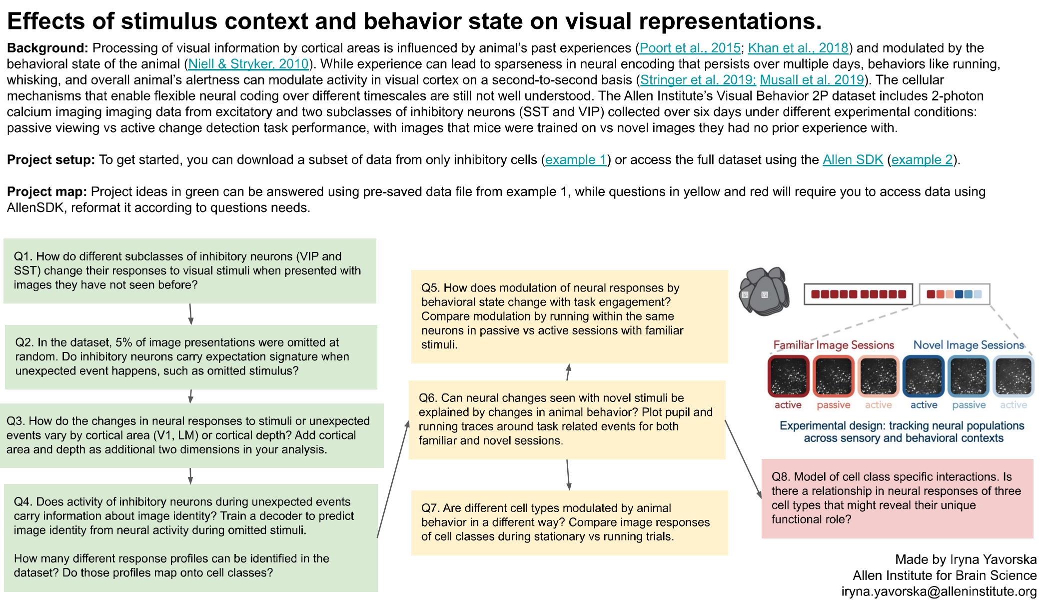
Project Templates

Click on each image below to see a full browser version!

Flow of information through the brain during a sensorimotor task



Effect of stimulus context and behavior state on visual representations



Behavior representations in mouse visual cortex

Contents

Behavioral representations in mouse visual cortex

Background: Mouse move their whiskers, groom, and run while we record their neural activity. These behaviors are represented in neurons across the brain, not just in motor areas. In particular, we will be analyzing neural activity in the visual cortex. You can see more details about this dataset in the intro video and in the associated paper. There are ~10,000 neurons recorded simultaneously across multiple cortical depths, along with the facial behaviors of the mouse, represented using the principal components of the motion energy. We want to understand what types of behaviors are represented by the neurons, and how they are represented. This may give us clues as to how these signals might be used for computations such as learning associations between behaviors and visual stimuli. To do this, we can build various models to decode behavior from neural activity.

Project setup: This project will use this data loader.

Project map: description of the suggested questions and how they relate to each other and to the project. The tree structure can and should be customized as necessary for each project.

Q1. Train a decoder to predict the mouse's pupil area. This is a 1-dimensional variable to predict, we can build a linear decoder from neural activity (see W1D4).

Q2. Are you able to fit well? Try adding an L2 penalty (ridge regression) to improve the fit (also see W1D4).

Q3. Which neurons in visual cortex contain the most information about pupil area? Compute the decoding accuracy from neurons at different cortical depths.

Q4. Train a decoder to predict the mouse's eye position. Can we do a good job? Why might it be useful for visual cortex to represent this information, if it does?

Q5. What other facial movements of the mouse can we predict? Let's try training a linear decoder from neural activity to motion energy (dat['beh_svd_time']).

Q5. What other facial movements of the mouse can we predict? Let's try training a linear decoder from neural activity to motion energy (dat['beh_svd_time']).

Q6. Is a linear decoder sufficient to predict facial movements? Try training a non-linear decoder using a neural network with a single hidden layer (W2D1). If it does better, what does that imply about the behavioral representations in visual cortex?

Q7. To better understand which behaviors are represented, cluster the facial movements using k-means, or running UMAP then running DBSCAN. Determine which clusters are best predicted by neural activity.

Q8. Alternatively discretize facial movements using an HMM (e.g. see this paper, also see W3D2). Determine which states are best predicted by neural activity.

Q9. (Theory) Simulate a neuronal network (see W2D4) that receives as input the HMM states with a percentage of positive weights across neurons. What sorts of connectivity (high recurrency / low recurrency) may limit the ability to linearly readout a state? Will it depend on how long the state is active for and will it depend on the number of neurons driven by the state?

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Mapping brain activation and representation with fMRI

Mapping brain activation and representation with FMRI

Background: Stimulus-evoked activity can be measured with FMRI through haemodynamics: changes in blood flow, volume, and oxygenation in response to neuronal activity changes.
Project setup: Here we start from time series data. Using the HCP task data, where different stimuli are either ON or OFF, we will create increasingly sophisticated models of brain activity. We will then use these model to ask statistical questions on localisation of brain function and on information representation.
Project map: The project core is covered by Q1-4; subsequent questions can be taken in any order. If using data sets that have beta maps, you can start from Q5-6

Q1. Calculate the average activity levels during presentation of the stimulus and compare to when the stimulus is off. Contrast different brain areas. Generate summary plots etc.

Q2. Use a T-test to formally test which regions' activity is significantly modulated by the stimulus, or significantly more for one stimulus type than another.

Q3. Set up a GLM where each regressor is a stimulus response model (e.g. ON-OFF) and regress this model against the FMRI time series data. Calculate the betas from this GLM and uncertainty on the betas. Use these to setup a statistical test for asking which regions respond to the stimulus.

Q4. Augment the GLM with a more realistic response profile by convolving the On-Off stimulus vectors with a haemodynamic response function (e.g. a Gaussian or Gamma function).

Q5. Use the estimated beta maps to calculate RDMs (representation dissimilarity matrices) and map their variations across the brain

Q6. Set up a linear decoder that can predict the stimulus type from the multivariate brain activity, either whole brain or dimensionality-reduced.

Q7. Design a statistical test that allows you to compare brain representations to a predefined template.

Q8. Contrast the results to an artificial neural network that is designed to solve a similar task/problem.

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Retinotopic mapping with FMRI

Retinotopic mapping with FMRI

Background: Multiple brain areas in the visual cortex contain a map of the visual/retinal space. FMRI is routinely used to estimate this mapping in order to delineate different subdivisions of the visual cortex and study their properties.
Project setup: This project is set to utilise a retinotopic mapping experiment, for which the Human Connectome Project data is used (see data loader and Benson et al. for a detailed description of the data/experiment)
Project map: The project core is covered by Q1-3; For Q4 see Dumoulin 2008.

Q1. Using a General Linear Model, calculate the magnitude and phase of the FMRI signal in every location of the brain.

Q2. Use the stimulus image files to adjust the phase of the stimulus. Use the borders of primary area V1 to validate.

Q3. Augment the model with convolution with a Haemodynamic response function to accommodate for the lag between neural and vascular responses.

Q4. Fit a population receptive field (pRF) model to estimate the visual receptive field size in each brain area.

Q5. The previous Q involves nonlinear fitting, which can be time consuming over many brain voxels. Replace the nonlinear fitting with a deep ANN that can output pRF parameters directly from the data.

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Modelling of navigational affordances and scene-selective responses

Computational modeling of navigational affordances & scene selective cortical responses

Background: As we move about the world, we use vision to determine where we can go in our local environment and where our path is blocked. In this project, our first goal is to identify which brain regions encodes the structure of navigable space in visual scenes using behavioral and fMRI data from Bonner and Epstein. The next goal is to identify a computational model of navigational affordances and underlying cortical responses
Project setup: Consider fMRI response to indoor images in the form of ROI specific and searchlight representational dissimilarity matrices (RDMs). Find which ROIs/ searchlights show significant correlation with navigational affordances behavioral RDM. Identify relevant computer vision models to explain navigational affordance behavioral and scene selective fMRI responses
Project map: The project core is covered by Q1-4; subsequent questions explore potential models to explain behavioral and scene-selective fMRI responses

Q1. Compare behavioral navigational affordance RDMs with ROI RDMs using Spearman's correlation. Which ROI shows highest correlation with affordance RDMs?

Q2. Compare behavioral navigational affordance RDMs with subject-wise searchlight RDMs

Q3. Perform a t-test to find out which searchlights show significant correlation with navigational affordance RDM

Q4. Input the stimulus to a computer vision model (e.g. AlexNet) and create layer RDMs. Correlate the model RDMs (Bonner & Epstein 2018) with fMRI and behavioral RDMs. Which layer shows the highest correlation ? Why?

Q5. Think of other relevant computer vision tasks that are more related to navigational affordances (e.g. Dwivedi et al. , Lescroart et al.). Perform the same analysis as previous steps and compare results.

Q6. Compare the two model RDMs. Do you observe a high correlation between them? Apply variance partitioning analysis to find how much of the variance of fMRI and behavioral RDMs these models explain uniquely.

Q7. Based on the functions of scene selective regions (Lescroart et al., Henriksson et al.) identify computer vision models that perform a similar function. Correlate with fMRI ROI RDMs and perform permutation test to validate your hypothesis.

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Visual information in different brain regions

Investigating the visual information in different brain regions

Background: Stimulus-evoked activity can be measured with fMRI through haemodynamics: changes in blood flow, volume, and oxygenation in response to neuronal activity changes. fMRI recordings allows recording responses from multiple brain regions simultaneously with high spatial resolution. In this project we look at the human fMRI response to visual stimulation and investigate which brain regions encode which type of visual information by predicting fMRI responses from artificial vision models.
Project setup: Consider fMRI response to visual stimulation (images/ videos) and a basic computer vision model (AlexNet) performing image classification. For images you can use Kay & Gallant dataloader, for videos you can use Algonauts dataloader.
Project map: The project core is covered by Q1-3; subsequent questions can be taken in any order.

Q1. Train a voxel-wise encoding model (Naselaris et al., Cichy et al.) to predict fMRI responses in different brain regions from different layers of Alexnet (Krizhevsky et al.).

Q2. Is visual cortex hierarchy related to model's hierarchy? Compare the predictions of individual layers for different regions by visualizing the results through a heatmap. Do you observe any pattern? (e.g. in Guclu et al. , Agrawal et al.)

Q3. Now try predicting fMRI response using a randomly initialized AlexNet model. Is the pattern you observe different from above? What role does training the model on image classification have on prediction performance?

Q4. Which brain regions preserve spatial information? Apply image transformations randomly before feeding to DNN and observe the change in encoding accuracy.

Q5. Which brain regions encode categorical information? The deeper layers of the model (fc6-fc8) are known to encode categorical information. .

Q6. Which brain regions encode action information? Find a model performing action recognition and compare encoding accuracy of different regions predicted by deeper layers.

Q7. Find which DNN units play a major role in encoding performance. Remove DNN units and investigate the impact on encoding performance

Q8. Visualize using lucid/network dissection what information is encoded in top units

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State-dependent decision-making in mice performing a 2AFC task

Investigating state-dependent decision-making in mice performing a 2AFC task

Background: The International Brain Laboratory studies perceptual decision-making in mice. They have collected millions of trials of mice making a binary choice based on a visual stimulus. Formally, this is called a two alternative forced choice (2AFC) task. While the mice learn to perform the task well, they still make many mistakes. This project will study these "lapses" in judgement to look for evidence of time-varying internal states, following recent work of Ashwood et al (2021) and Roy et al (2021).

Project setup: This project will use the IBL behavior dataset (intro, loader1, loader2, loader3)

Project map: The core project follows Q1-Q5, then branches into more involved models and analyses.

Q1. Fit a logistic regression for each fully-trained mouse to predict its choices given the stimulus contrast and a bias. This yields a classic *psychometric curve*. How well does the curve fit the data? Evaluate goodness of fit by comparing predicted vs empirical choice probabilities as a function of stimulus contrast (ignoring "violation" trials). Quantify performance with log likelihood on a test set.

Q2. How can you change the model to account for trained mice that still make mistakes, even on high contrast stimulus? Introduce a *lapse probability* into the logistic regression (eq. 1 of Ashwood et al, 2021), fit with gradient descent, and evaluate the model fit, and compare its performance on held-out data.

Q3. Are choices *autocorrelated*? Include past choice and reward into the logistic regression and reanalyze your model, comparing it to those from Q1 and Q2.

Q4. Is mouse behavior *stationary*; i.e. do mice seem to follow a single strategy? Fit the model from Q3 on sliding windows of data within a session. Do the parameters change significantly within a single session?

Q5. Does behavior change with the number of rewards received? For example, maybe mice become sated or "bored" over the course of the session. Do you see any evidence for such changes in *internal state*?

Q6. Are some mice more stationary than others? I.e. do some mice seem to use one strategy the whole time whereas others change their behavior throughout a session (as measured by the logistic regression parameters in each window)? Similarly, do labs show differences in stationarity of behavior?

Q7. Perhaps there is a "mental cost" to task engagement. Can you build a theoretical model to predict and explain changing behavior as rewards are accrued over a session?

Q8. Following Ashwood et al (2021), fit a GLM-HMM that allows for discrete internal states with different logistic regression parameters. Use EM to infer the states and estimate the model parameters. *Hint: you might want to start with a library like SSM.*

Q9. The HMM from Q8 assumes discrete changes in internal state, but satiety and engagement might be better described as continuous latent variables. Following Roy et al (2021), build a GLM with continuously varying weights and fit it to the behavior data.

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The working memory capacity of recurrent neural network models

Investigating the working memory capacity of recurrent neural network models

Background: To hold information in working memory or integrate sensory inputs over time, the brain must be able to maintain representations of past sensory inputs for several seconds for future computation (NMA: **W3D2**; Barak and Tsodyks, 2014). Recurrently connected networks of neurons have been shown to be capable of producing stimulus-evoked firing rate fluctuations on timescales many orders of magnitude longer than that of the membrane time constant of individual neurons (Toyoizumi and Abbott, 2011). In this project, we ask: what strategies might recurrently connected populations in the brain employ to preserve temporally structured information over time?

Project setup: link to Colab notebook

Project map: The project core is covered by Q1-5; subsequent questions can be taken in any order.

Q1. Train a decoder to predict the input identity at time (t-X) from the firing rate of the N neurons at time t, for various positive values of X. You should use a separate decoder for each X. Plot decoder performance as a function of X, for g=1.

Q2. Now, try varying the value of g- how does decoder performance change? Generate the plots from question 1 for several values of g.

Q3. Next, try tuning the input magnitude, or the number of cells in the network to receive input.. Generate plots of decoder performance for several values of these two parameters.

Q4. Rather than a single input pulse, consider a network receiving a stream of inputs over time. How do new inputs affect decoder performance for past inputs?

Q5. Consider the input to your network. Different input values could be passed as pulses of different magnitudes, or as inputs to different subsets of neurons. Which input form can persist for longer?

Q6. We initially assumed Gaussian random weights in our network. How does memory capacity change if we enforce Dale's law?

Q7. A linear decoder can only tell us so much. To incorporate nonlinear effects, compute the mutual information between network firing rates and the input identity, as a function of time, for multiple values of g.

Q8. What kinds of solutions do we get if we train network weights to maximize memory instead, eg using FORCE? How does memory capacity change?

Q9. Test unsupervised plasticity mechanisms such as Hebbian/anti-Hebbian/asymmetric synaptic plasticity. How does memory capacity change?

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Attractor models of working memory

Attractor models of short-term memory

Background: Persistent, stimulus-dependent neuronal activity has been observed in some brain areas during tasks (that require) requiring the temporary maintenance of information. This function is called short-term memory. Neurons representing the information can remain active for several seconds after the original input has been removed. In this project you will build a simple, population-based, dynamical system model of a short-term memory task (NMA: W2D4). You will study how even a simple model can generate different behaviors. This project requires basic proficiency in the mathematics of dynamical systems.

Project setup: <link to a google colab>.

Project map: Q1-5 cover the core part of this project. Additional questions may emerge while tackling Q1-5. Explorations are encouraged.

Q1. Simulate a dynamical system consisting of two excitatory units and one inhibitory unit connected to both excitatory units. Use firing rate equations and a sigmoidal nonlinearity as the transfer function. Allow each unit to receive an external input.

Q2. Calculate and plot the two nullclines of the system, assuming that the inhibitory unit membrane instantaneously integrates all inputs.

Q3. Find a set of network parameters that allows the network to perform a binary task with short-term memory . Deliver a positive stimulus to either of the excitatory units to simulate the two trial types. What parameter(s) can you vary so that the network displays two fixed points? How do you push the network activity towards one of the fixed point?

Q4. Verify the stability of the network by perturbing its activity with a transient stimulus. Can you make the network robust to perturbation of the inhibitory unit (mimicking an optogenetic perturbation experiment). Can you make the activity switch between fixed points?

Q5. The value of the membrane time constant typically lies within the 5-150 ms range. However, neuronal activity appears to evolve on a slower (>500 ms) timescale in short-term memory tasks. Can you tune the weights so that the network activity evolves toward the stable fixed-points on a timescale slower than the typical membrane time constant?

Q6. A different proposed mechanism for short-term memory relies on line-attractors. Can you tune the network so that it produces a line attractor? Instead of a sigmoid, try using a rectified linear transfer function. Does this help?

Q7. Short-term plasticity occurs when the availability of neurotransmitters varies over time, causing a history-dependent increase or a decrease of the firing rate. Study the network after adding short-term facilitation (STF) and short-term depression (STD). How do STF and STD change the shape of the nullclines? How does the dynamic change? Does the activity at the fixed-point still appear steady?

Q8. Add a slowly ramping external input to the excitatory units. Find a set of parameter values that make the network switch from one to two stable-fixed points (i.e. that will cause a *bifurcation*) as a function of the external input value.

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Does neural activity reflect face perception?

Does neural activity reflect face perception?

Background: It is all too easy to find a neuron in the brain representing sensory features of the external world. This especially applies to visual cortex, where it has been shown that neurons in the mouse brain encode stimulus orientation to an average precision of 0.3 deg, which is 100x better than the mouse's behavioral performance (see Stringer orientations dataset, Stringer et al, 2021). However, just because a population of neurons encodes a stimulus does not mean that the subject has conscious access to this information. When a subject is aware of a stimulus feature, we say that the subject has formed a "percept". Can we find areas of the brain where neural activity correlates with perception, measured psychometrically by the subject's performance in a task? In this project, you will answer this question for the Faces/Houses ECoG dataset (Miller et al, 2017), which contains stimuli with different noise levels as well as psychometric performance of the subjects viewing these stimuli.

Project setup: Use the data loader to investigate the ECoG responses.

Project map:

Q1. Make a plot of the average responses of each electrode to faces and houses without noise (first experiment). Decide on the right time period to include for analyses, which distinguishes faces and houses.

Q2. Formulate a selectivity index that tells you how well a given electrode distinguishes between faces and houses.

Q3. On the noisy face data, make average responses for faces and house for subsets of noise fractions (i.e. 0 to 0.2, 0.2 to 0.4 etc). Compute your selectivity index again as a sanity check that the same electrodes are selective.

Q4. Now compute the psychometric performance of the subject based on the fraction of true positives (correctly identified a face, TP) and false negatives (responded to houses thinking it was a face, FN).

Q5. You now have all the ingredients to compare the visual responses to noisy images of faces, with the subject's performance for a given noise level.

Q6. Can you predict a subject's mistakes on single-trials based on a single-channel of neural responses to the stimulus? If so, the neural activity might be directly reflecting the noisy perception.

Q7. Make a model of each electrode's trial-to-trial variability based on the subject's responses. Compare this to a null model where each channel responds with its trial-averaged PSTH on every trial. If your model with single-trial variability predicts more variance, does that mean the behavioral response influences the neural activity, or the other way around?

Q8. Same as Q6 but now combining information across channels. You might need some kind of decoder for this, choose the right one from sklearn. Try to estimate how much the performance *should* improve if the information in each channel was independent from other channels.

Q9. Are different electrodes correlated in the way they predict behavioral mistakes? Try to predict

Q10. Now to answer the big question: does neural activity in the fusiform gyrus reflect face perception, or does it merely reflect the subject's motor response? Use the reaction time information to parse early vs late neural activity and repeat all analyses.

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The structure of mouse social behavior

Analyzing the structure of mouse social behavior

Background: Animals engaged in social behavior make continuous decisions of how to interact with a member of their species. In the field of ethology, we study the structure of animal behavior to gain insight into the neural algorithms by which that behavior is controlled (see eg Anderson and Perona 2014; W3D3). In this project, you'll explore mouse behavior in a resident-intruder assay, in which a male mouse in its home cage is presented with a male or female intruder, and the animals are allowed to freely interact. Can you determine from tracking data what cues shape animals' behavior? What timescales of behavior can you identify in the data?

Project setup: Use the CalMS21 dataset (Sun et al 2021) to study the structure of mouse social behavior. The poses of both animals have been tracked using a computer vision pipeline (Segalin et al 2020), and three social behaviors of interest (attack, mount, and sniffing) are manually annotated. Code to load and explore the dataset is provided here**.**

Project map: An example project exploring timescales of behavior is outlined below- however feel free to get creative and follow other lines of investigation!

Q1. Visualize behavior rasters for several example sequences, and plot likelihood of observing attack, mounting, and sniffing as a function of time since sequence start, for all sequences > 8 minutes long. Does behavior look stationary?

Q2. Create and visualize some hand-crafted features characterizing animal pose- such as velocity, joint angles, inter-animal distance, etc (see Segalin et al 2020 for more ideas.)

Q3. Compute event-triggered-averages of some of your features, triggering on onset or termination of attack/mounting/sniffing. Do you see any features that seem modulated by behavior?

Q4. Are all bouts annotated for a given behavior the same? Try clustering frames or bouts of a behavior like attack or sniffing into "subtypes" based on the values of the features you created (You may want to look at average feature values across the bout, feature value at bout onset, etc.) Can you identify classes of aggression/investigation/mounting? (You should omit "other" from this analysis.)

Q5. Create a transition matrix characterizing transitions between behaviors, including the behavior subtyps you identified in Q4 (omit "other" for this analysis).

Q6. Revisit Q4, but now see if you can identify any meaningful "subtypes" of the "other" category; start by considering the pose of one mouse at a time, and omit "other" frames that are close in time (within ~2 seconds) to annotated frames for simplicity. Can you detect any interesting behaviors like grooming or rearing?

Q7. How non-Markovian are mouse behaviors? Compute the long timescale transition matrix: p(behavior N == X | behavior N-k == Y) for k = 5, 10, … as in Figure 2 here. How do these compare to the predicted matrices you'd get assuming the system is Markovian?

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