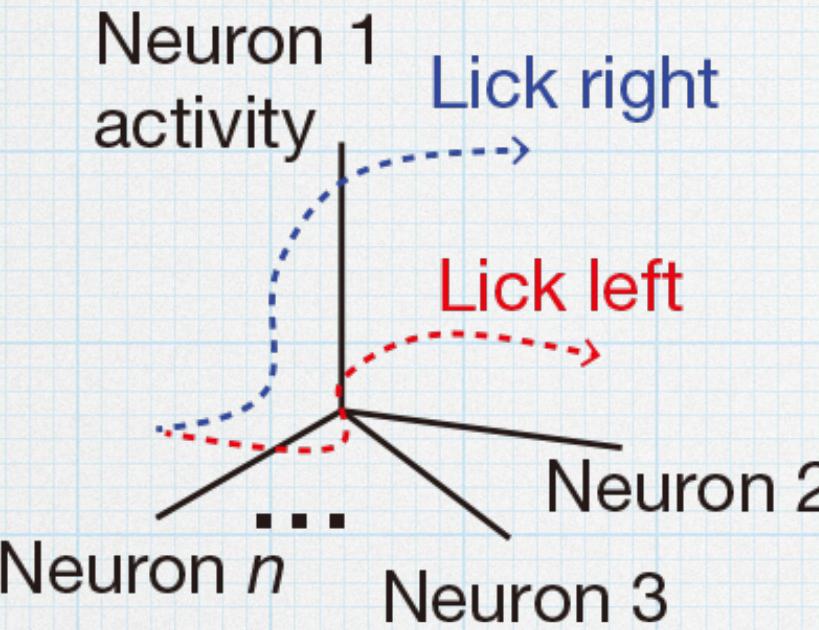


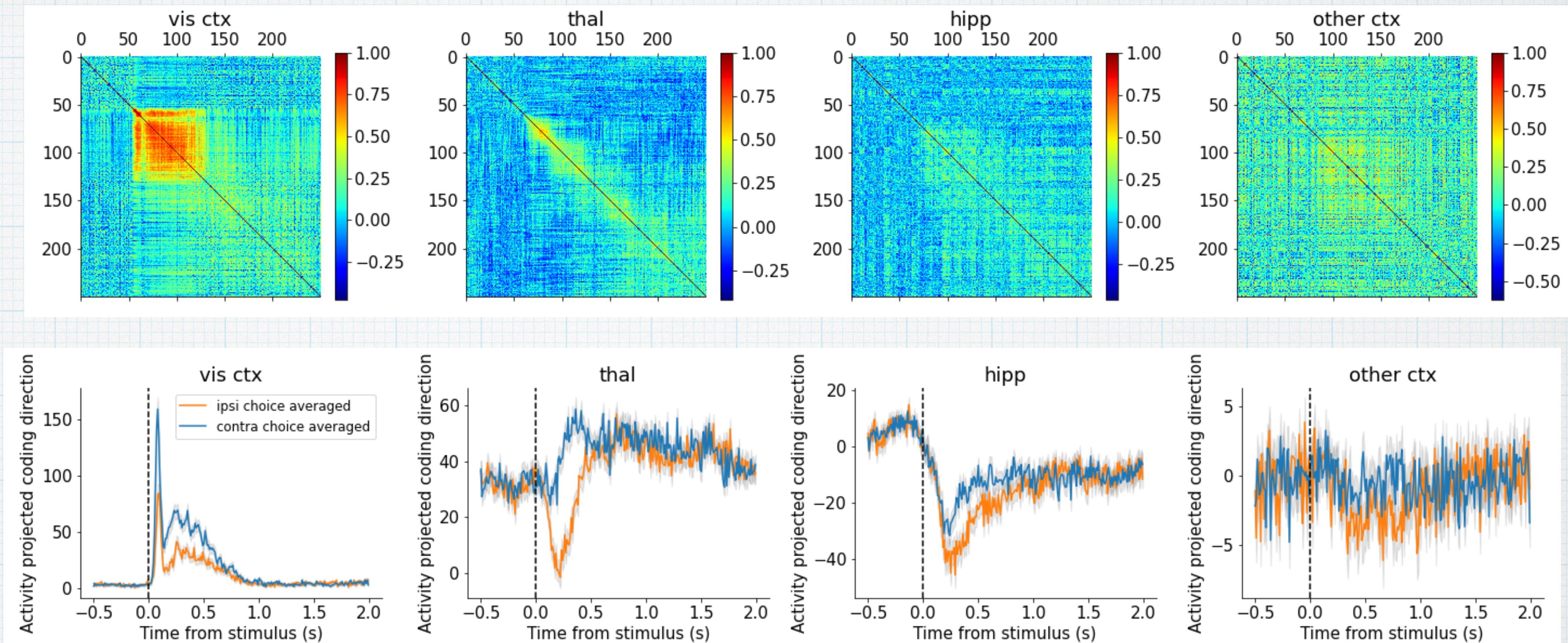
Latent dimensionality of decisions

- * Scientific question:
How do the trajectories of latent variables within brain regions, and shared across brain regions, change during different epochs of the task? And how are they correlated with behavior?
- * Scientific background: It remains a big question how much of the information in one brain area is shared with other brain areas, and how this may change with behavior or internal states.
- * Analyses: one-dimensional decoder, factor analysis (GPFA), PCA
- * Conclusions: Trajectories of latent variables extracted from the data in different brain areas during different epochs reflected the correlations between behavioral choices and the function of different brain areas.
- * Dataset: Steinmetz, 2019
- * Team members: Xiao Yao, Jiayu Guo, Tingyu Li, Baoqing Lu

Coding direction correlation across time (one session)



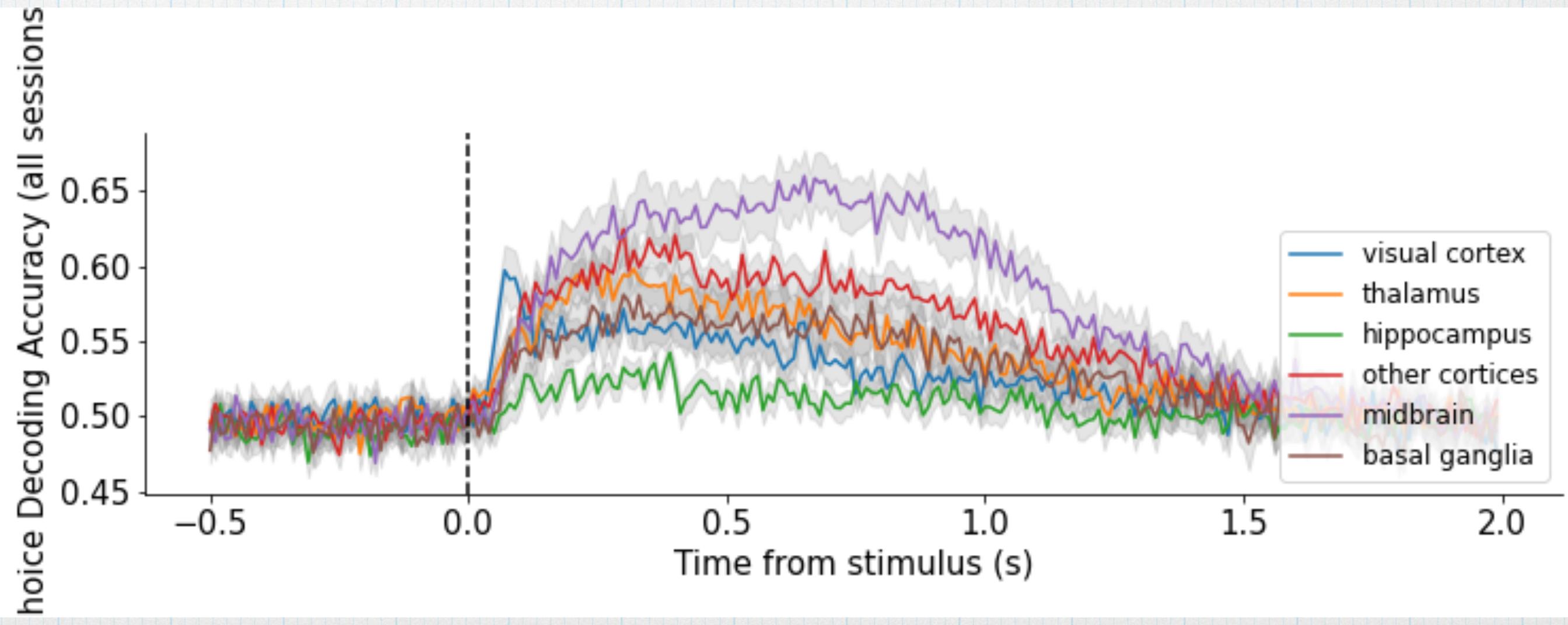
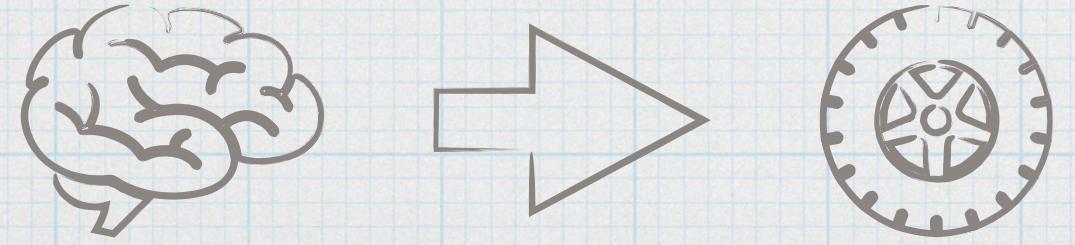
Coding direction projection of each brain region's neuronal population activity for two kinds of trials (one session)



Choice decoding accuracy using coding direction projection and decision boundary (all sessions)

$$DB = \frac{\mathbf{CD}^T \mathbf{x}_{\text{lick right}} / \sigma_{\text{lick right}}^2 + \mathbf{CD}^T \mathbf{x}_{\text{lick left}} / \sigma_{\text{lick left}}^2}{1 / \sigma_{\text{lick right}}^2 + 1 / \sigma_{\text{lick left}}^2}$$

(Li et al., 2016)



Question:

How does the brain encode the stimulus?

Methods:

Extracting the latencies by GPFA (Gaussian Process Factor Analysis) from the data in visual cortex.

Result1:

With right stimulus, the latency1 and latency2 will come up with a peak after onset, but not with left stimulus or without stimulus.

Result2:

With left stimulus or without stimulus, latency1 and latency2's amplitudes are smaller than with right stimulus or with both sides.

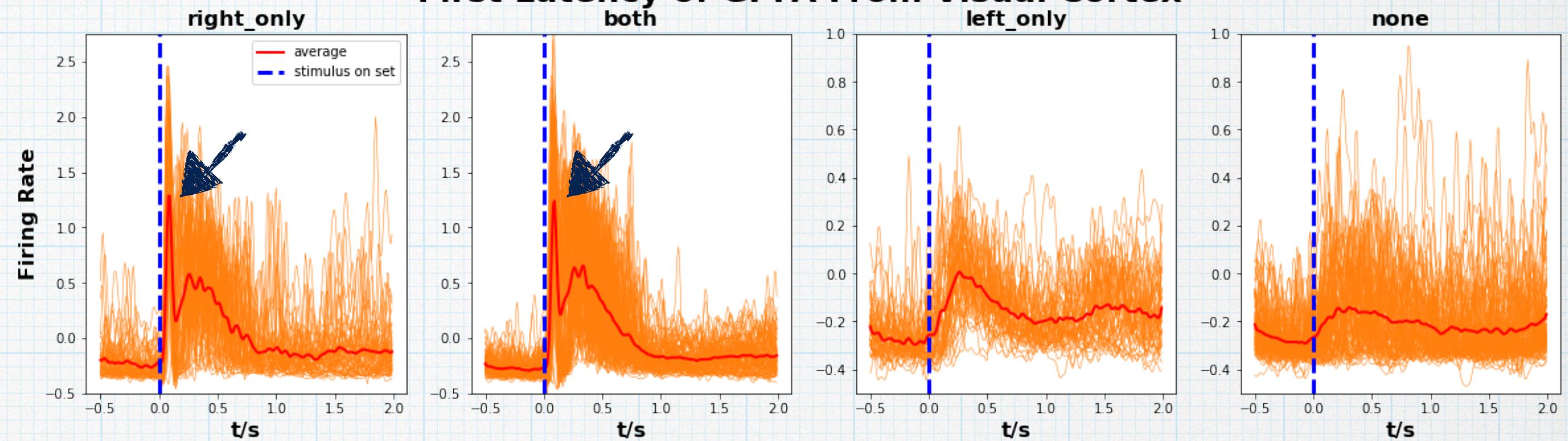
Result3:

With left stimulus, after stimulus onset, the latency will rise slightly higher than without stimulus.

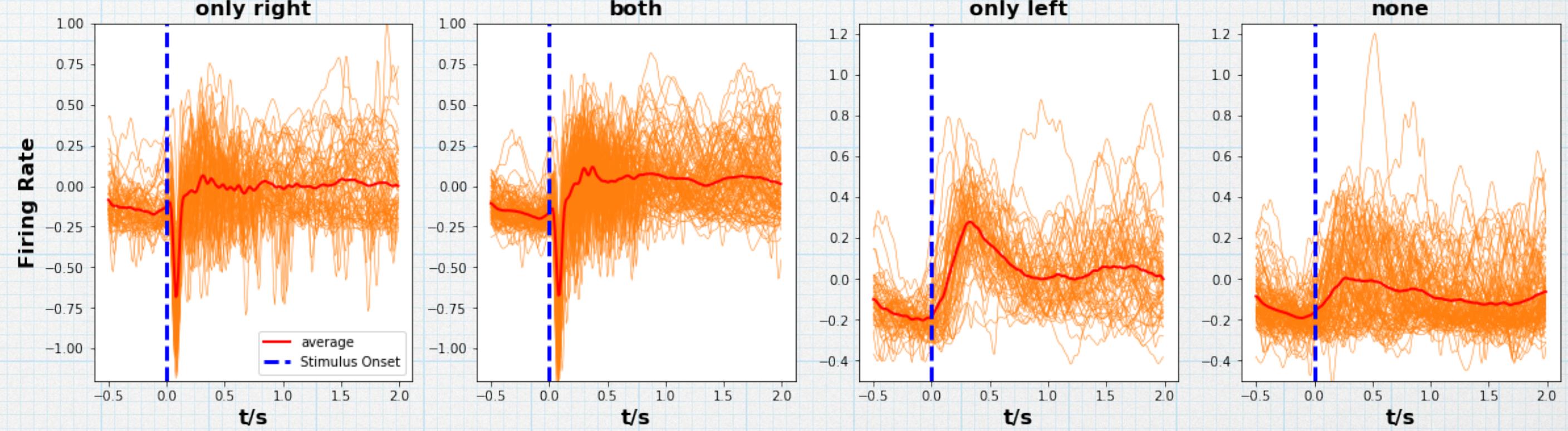
Guess:

The probes recording visual cortex's signal concentrate in mice's left hemisphere.

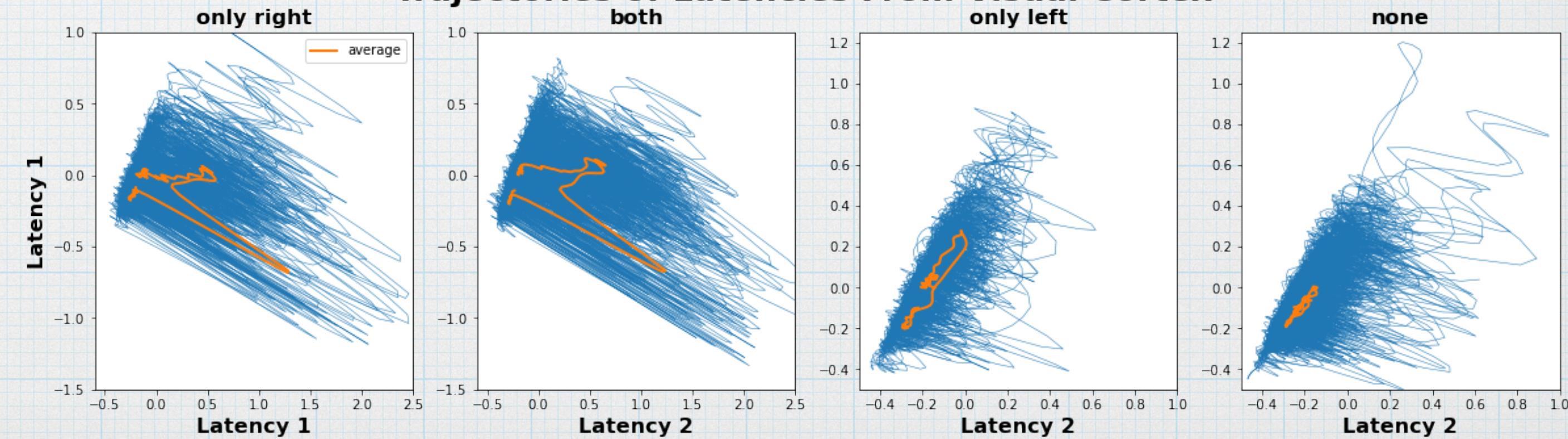
First Latency of GPFA From Visual Cortex



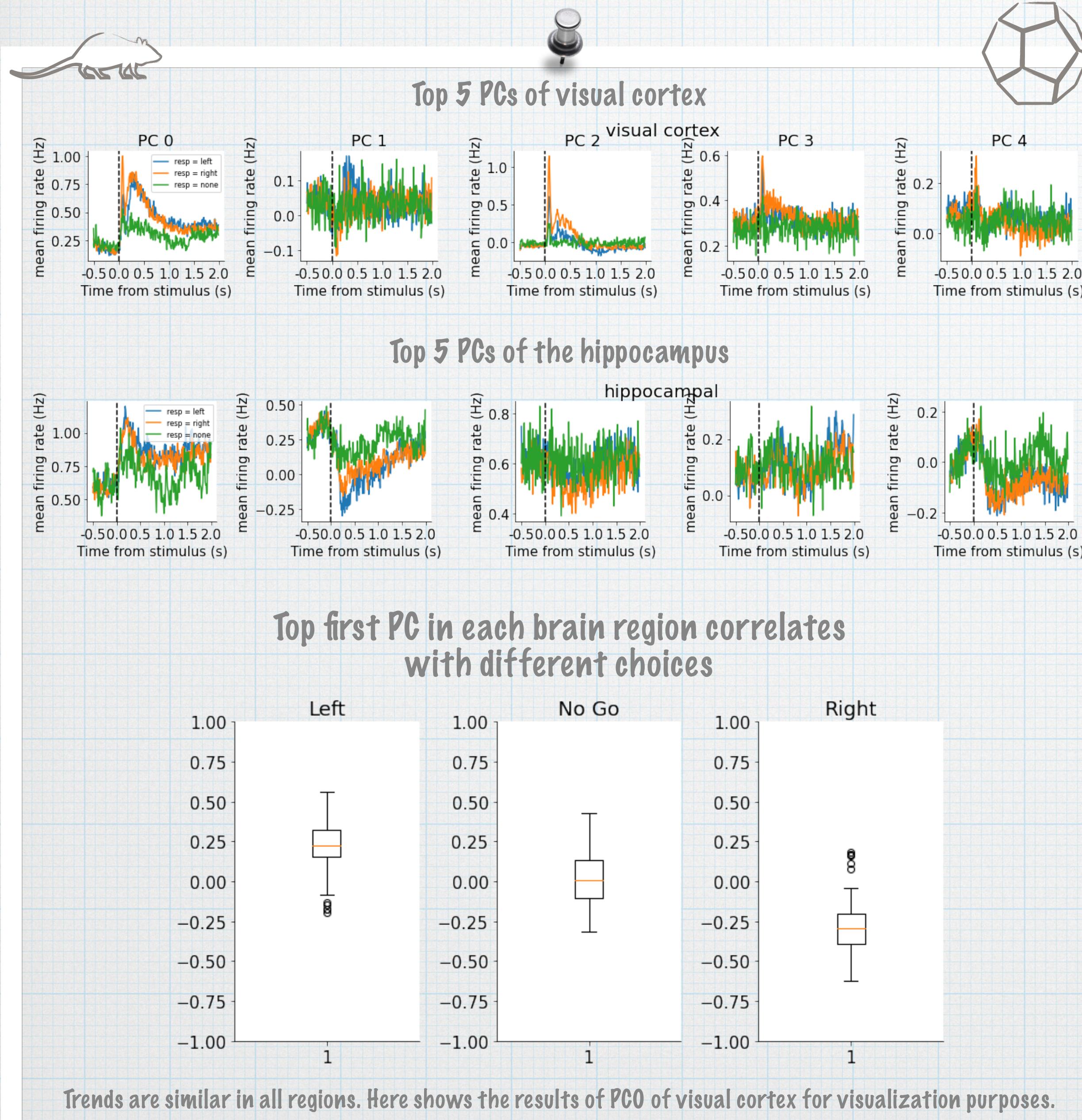
Second Latency of GPFA From Visual Cortex



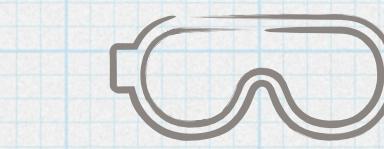
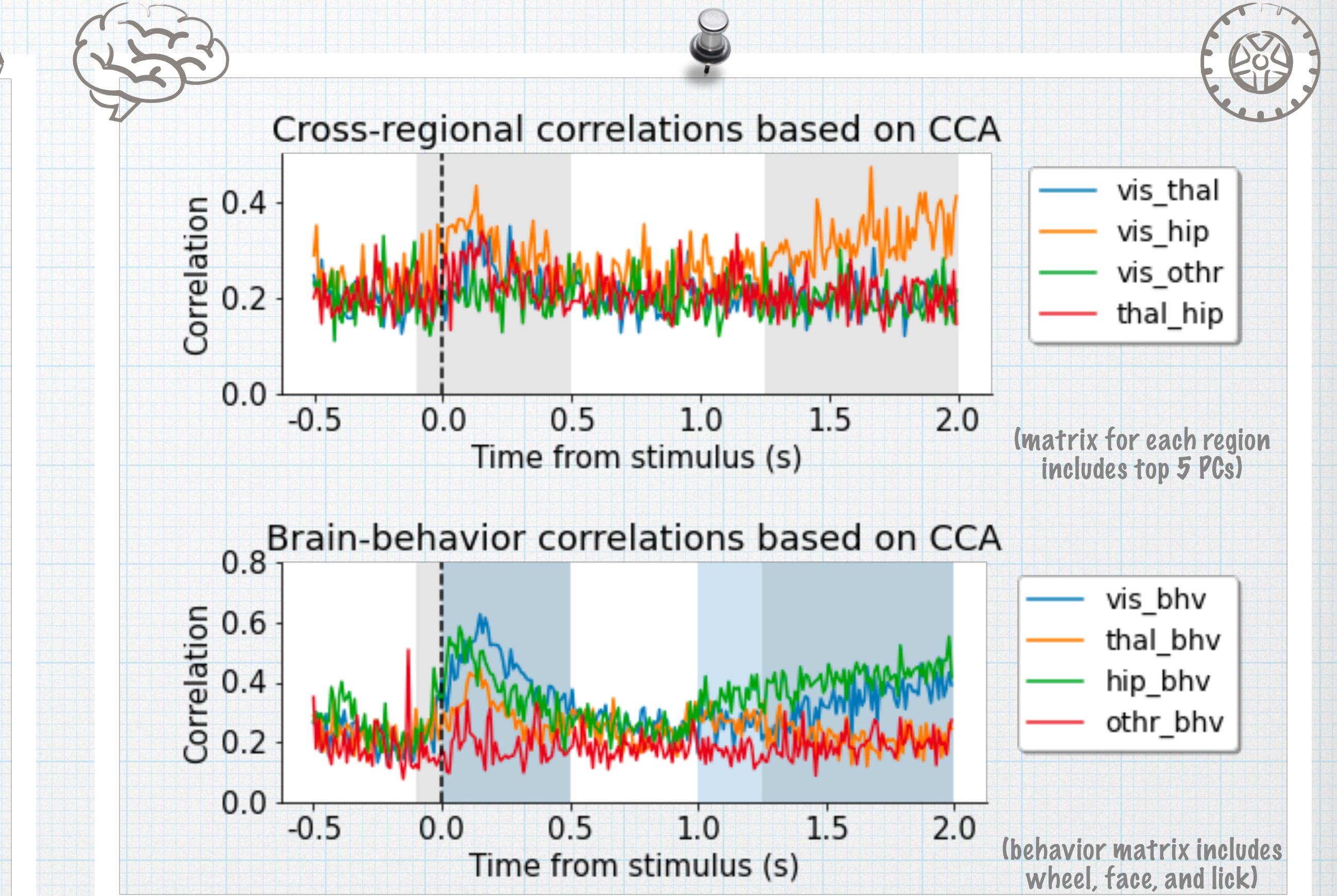
Trajectories of Latencies From Visual Cortex



Principle components of each brain region correlate with choices



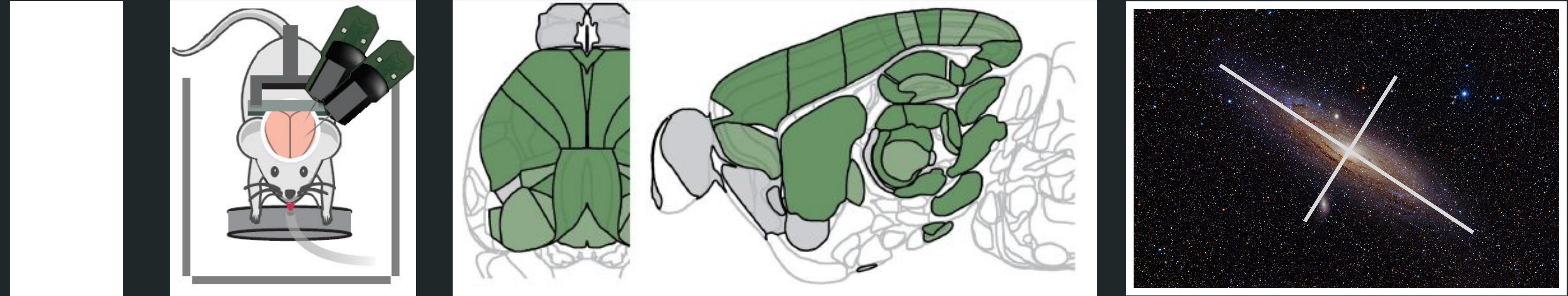
Neural activities across the brain are correlated with behavior in two time windows



Some other interesting findings

- ★ To reach 80% cumulative variance, visual cortex needs 40 PCs, thalamus needs 40 PCs, hippocampus needs 50 PCs
- ★ Realigned latent variables (canonical correlation analysis, CCA) correlate with behavior better than single principle components
- ★ PCA reveals similar time windows of neural activities as GPFA and vector decoder do

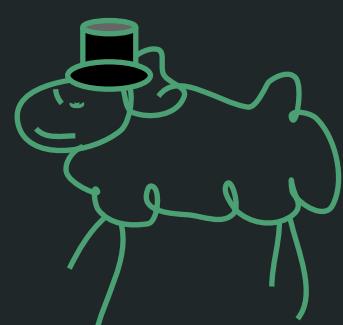
Behavioural variables correlate with intrinsic dimensions across diverse brain regions*



* Neuropixels dataset: Steinmetz, et al. (2019). *Nature*

Charlie Dowell¹, Ashley Kees², David Wolf³, Roberto Maffulli⁴, and Mohammad Bashiri⁵
Asaph Zylbertal (TA) and Uri Maoz (Mentor)

Pod: Classy-Wolf | Group: Classy-Sheeps



1 University College London, England

2 Université de Bordeaux, France

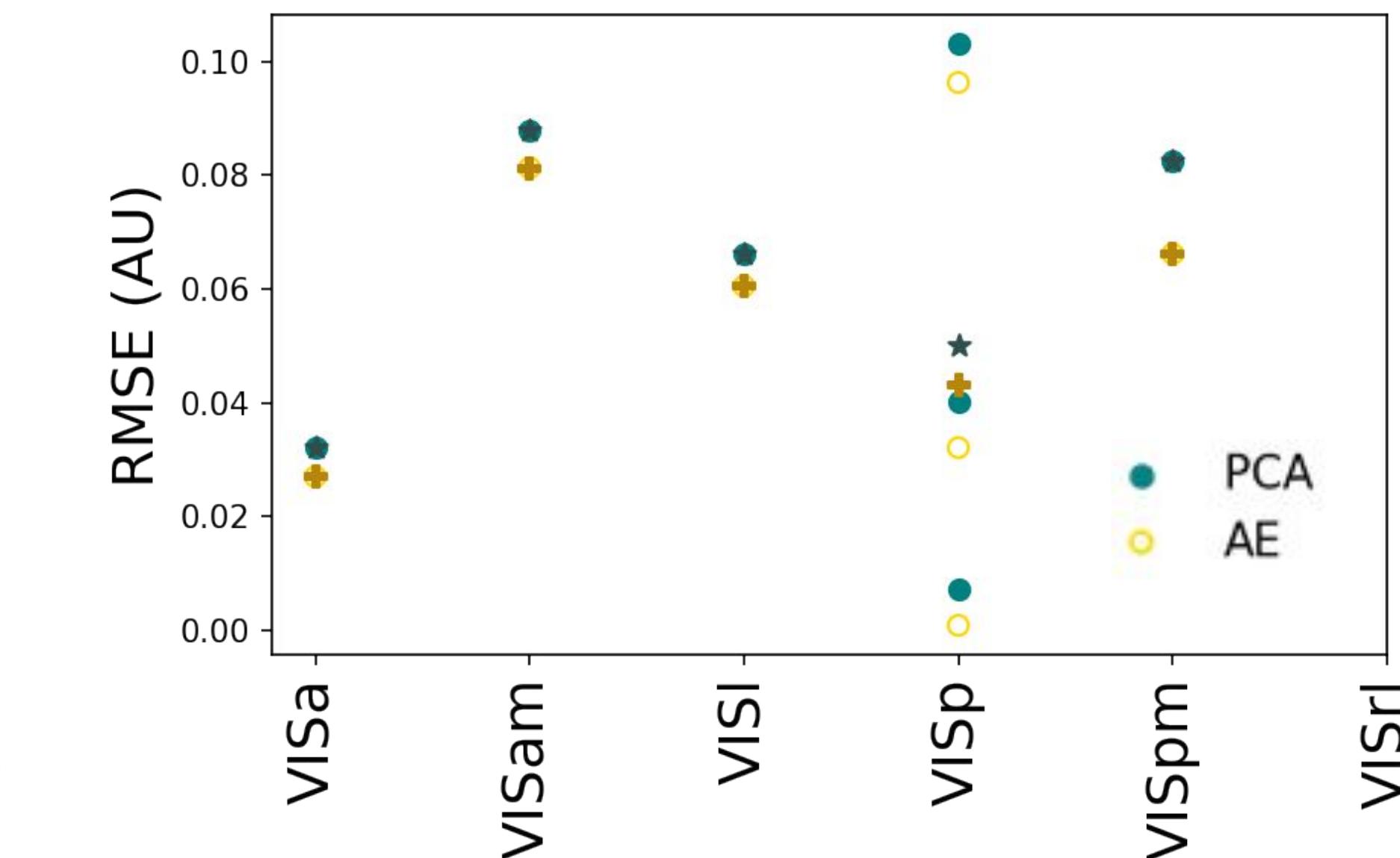
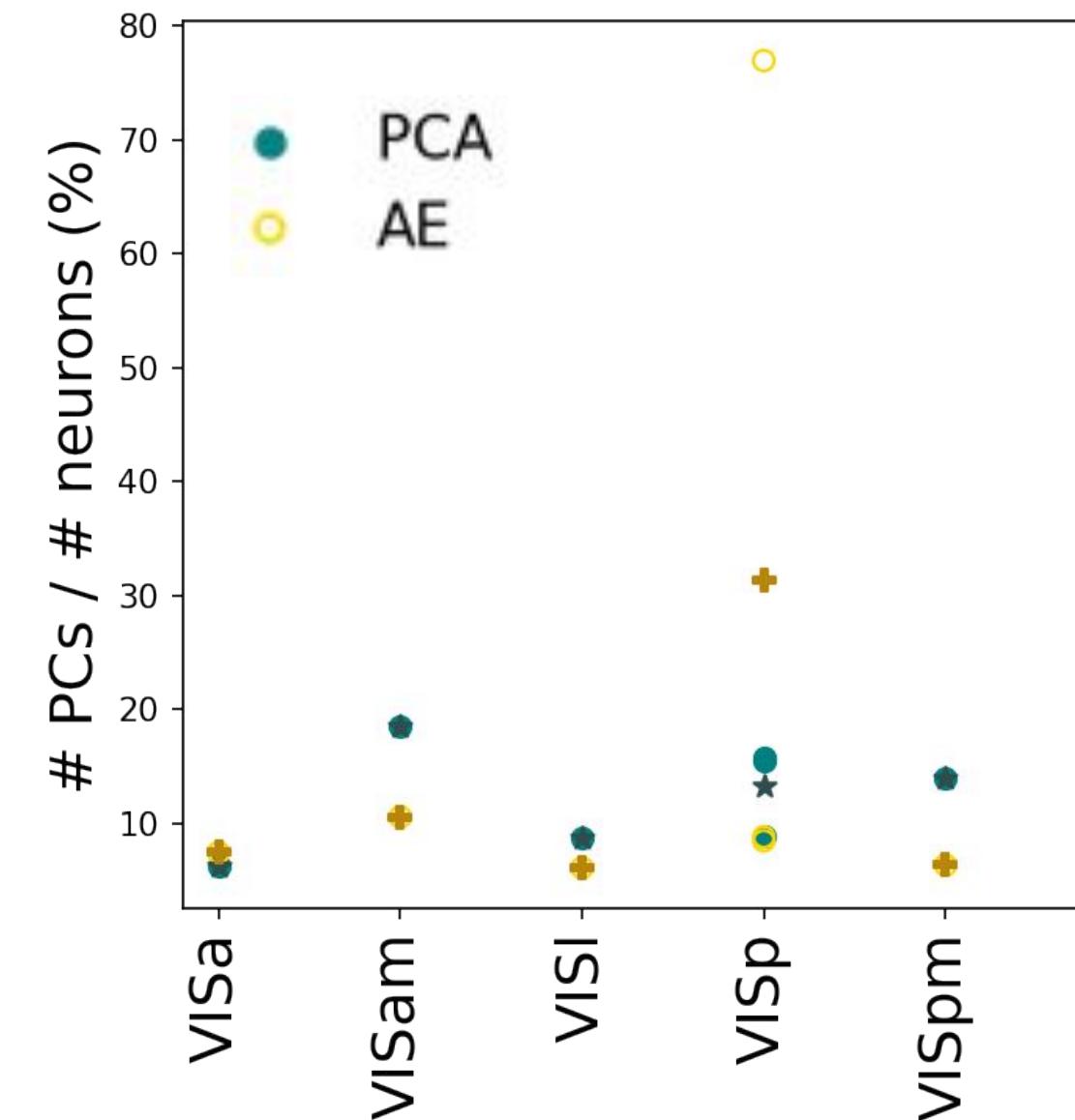
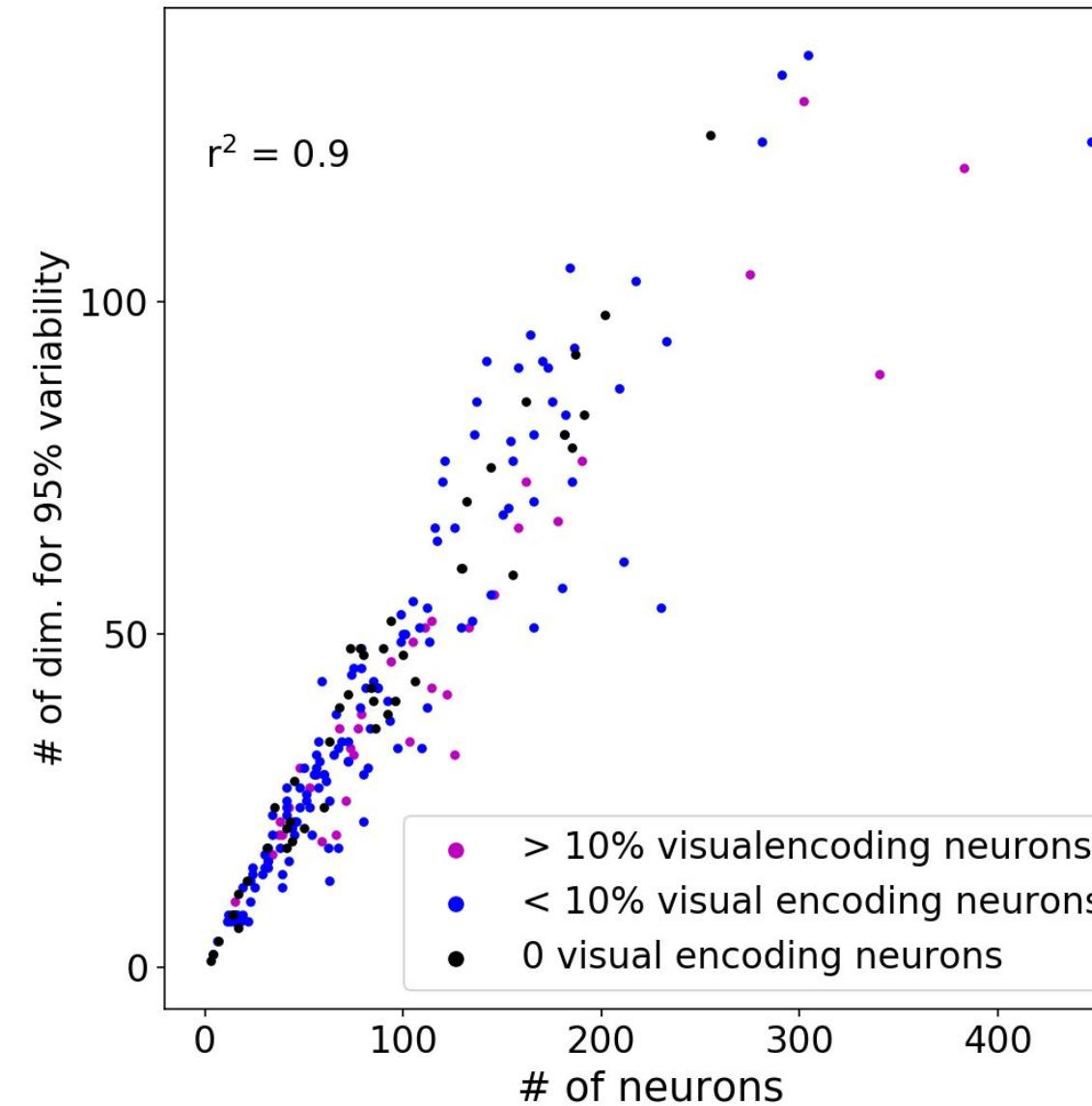
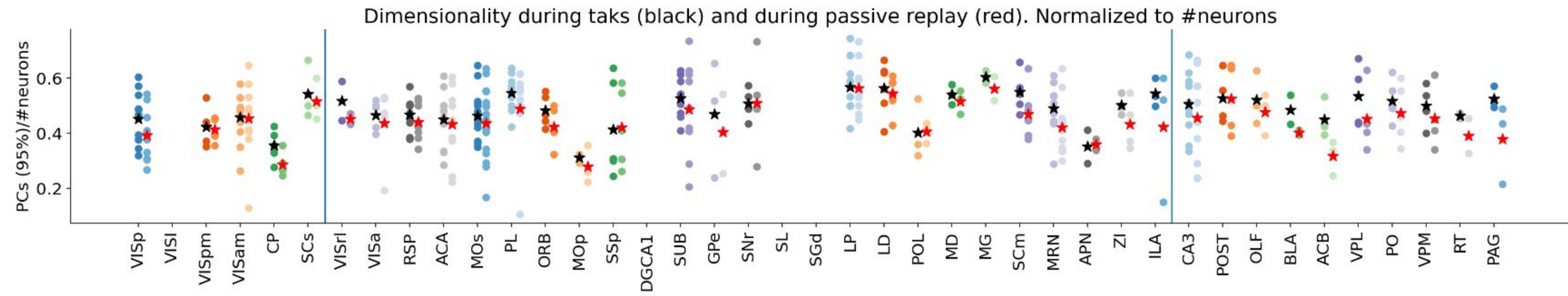
3 Central Institute of Mental Health, Germany

4 Istituto Italiano di Tecnologia, Italy

5 University of Tuebingen, Germany

Neural Population Data lies on a low-d manifold - but how does it vary across brain regions and behavioral states and can we identify the latent variables that give rise to it?

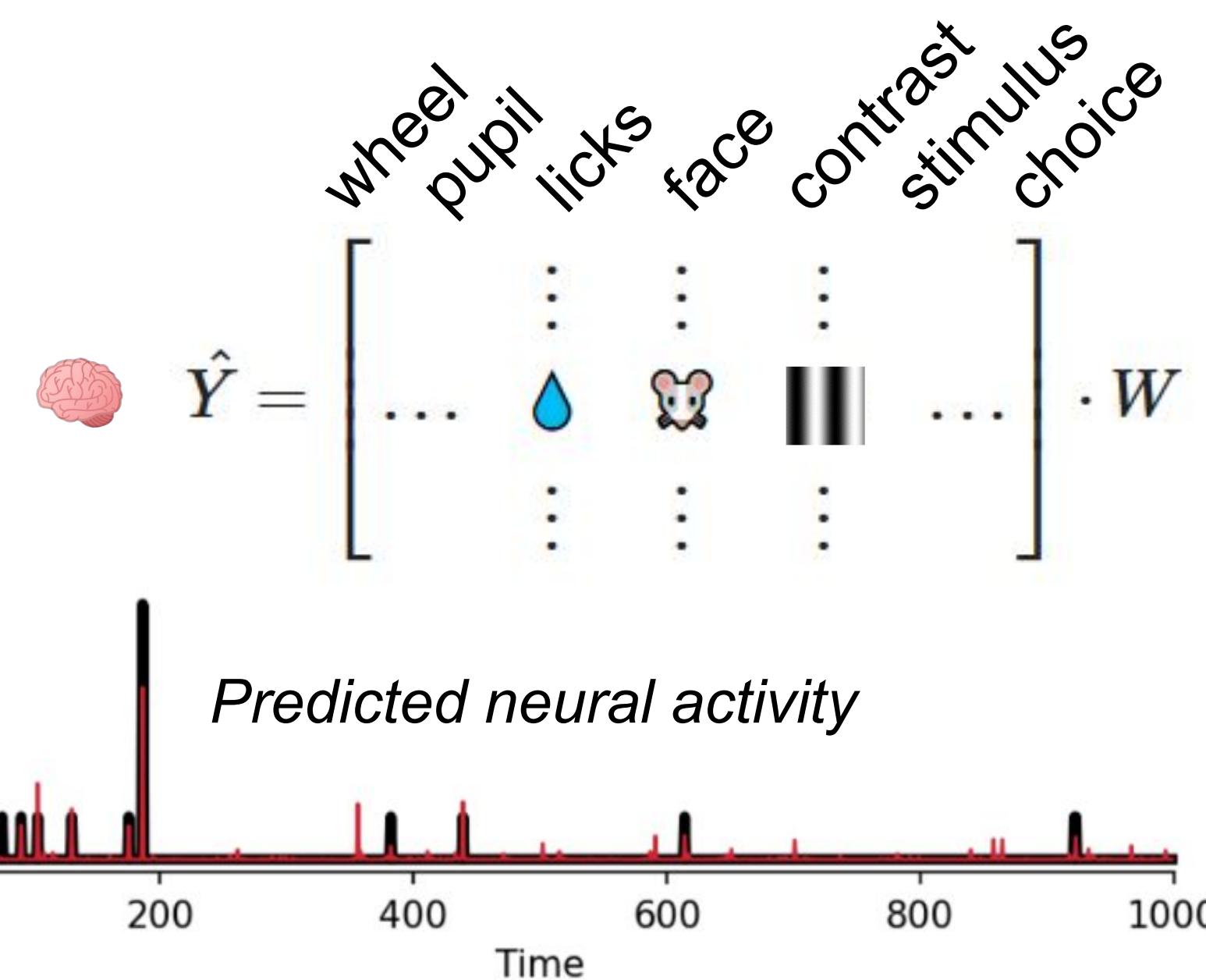
The fraction of PCs needed to explain 95% of the population's variance (~ the geometry of the intrinsic low-d manifold) varies between brain regions and behavioral states and is correlated to the number of recorded neurons.



Can we relate the latent variables identified in the experimentally recorded neural population by PCA to observable behavior (e.g. wheel speed, stimulus, task choice)?

1

GLM encoder to predict neural activity from behavioral/task variables



2

Find orthonormal basis of Covariance Matrix of recorded neurons

$$\text{cov}(\mathbf{Y}) \rightarrow \mathbf{V}_{exp} = \begin{bmatrix} \vdots & \vdots & \vdots \\ \mathbf{v}_1 & \dots & \mathbf{v}_n \\ \vdots & \vdots & \vdots \end{bmatrix}$$

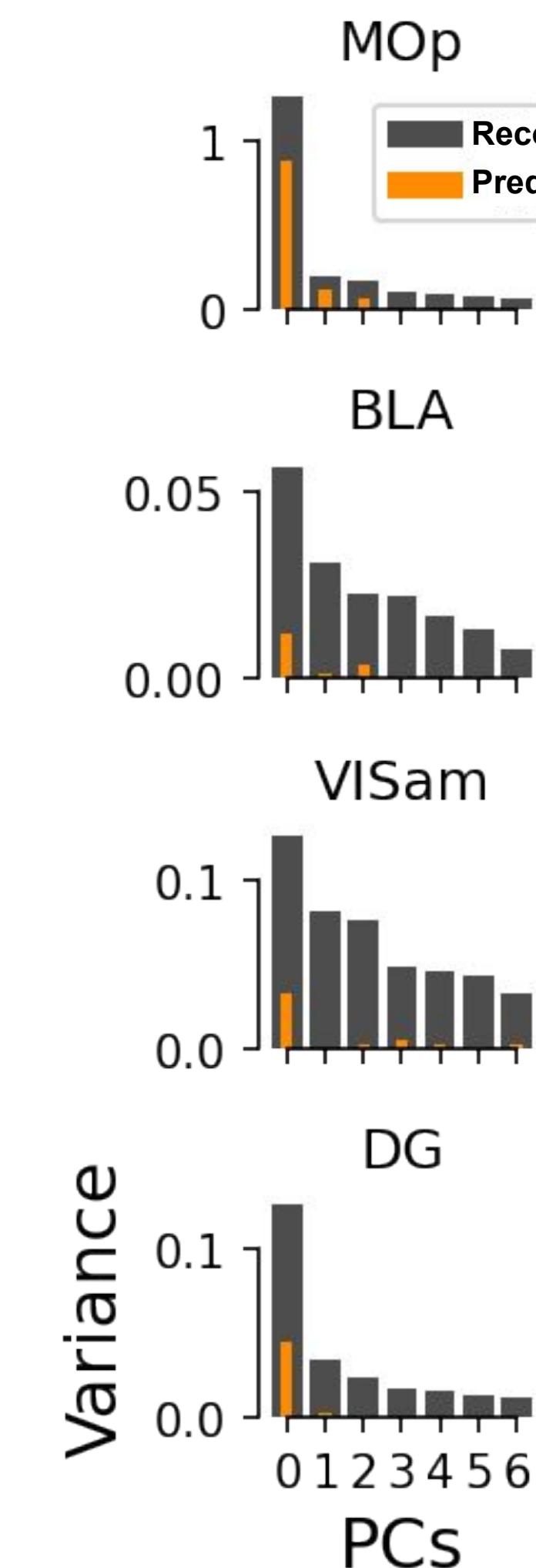
3

Project Predicted and Recorded activity onto the orthonormal basis

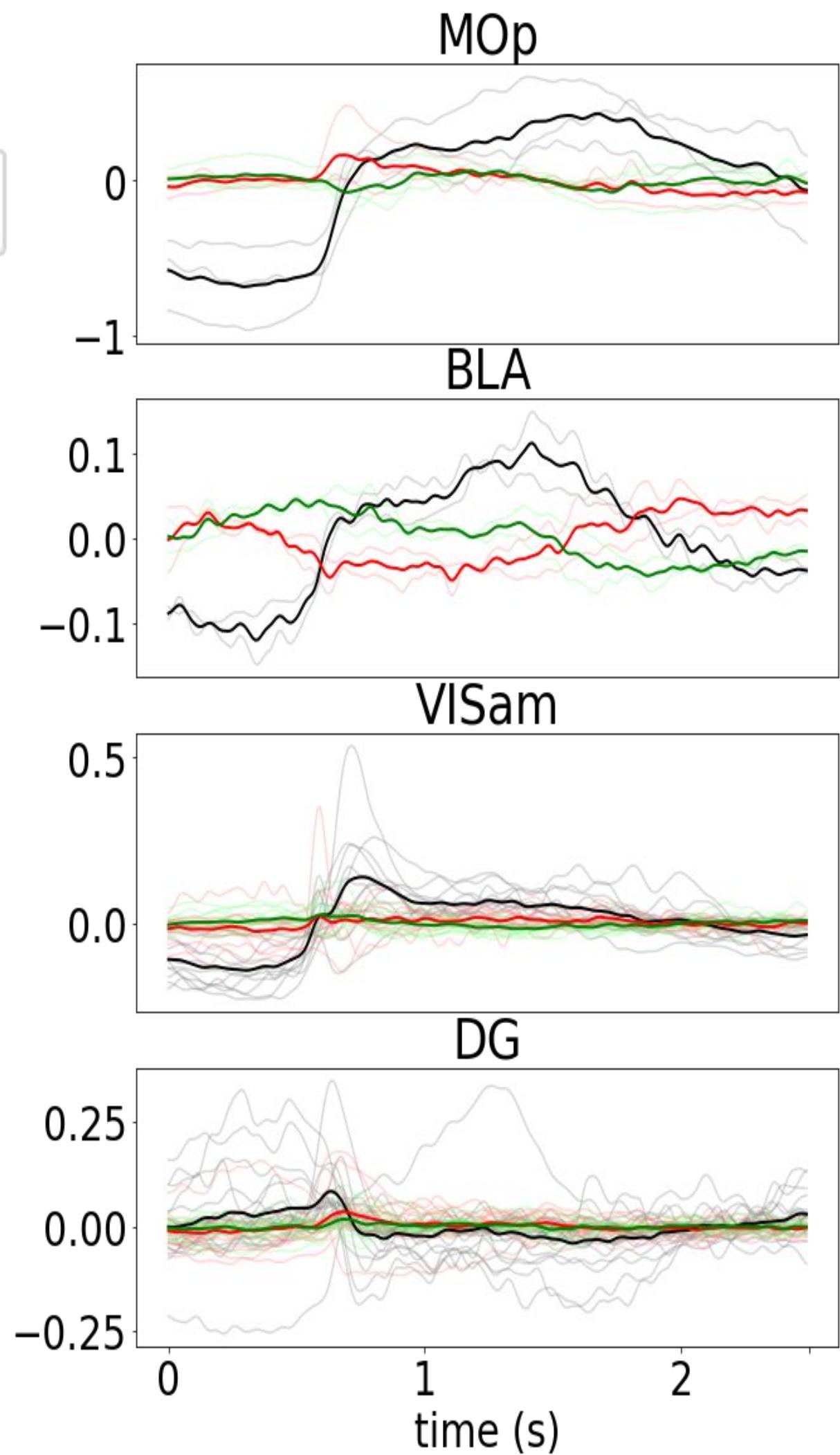
$$\mathbf{Y} \cdot \mathbf{V}_{exp} \rightarrow \mathbf{Y}_{proj}$$

$$\hat{\mathbf{Y}} \cdot \mathbf{V}_{exp} \rightarrow \hat{\mathbf{Y}}_{proj}$$

Compare variance along each basis for Predicted vs Recorded Population Activity



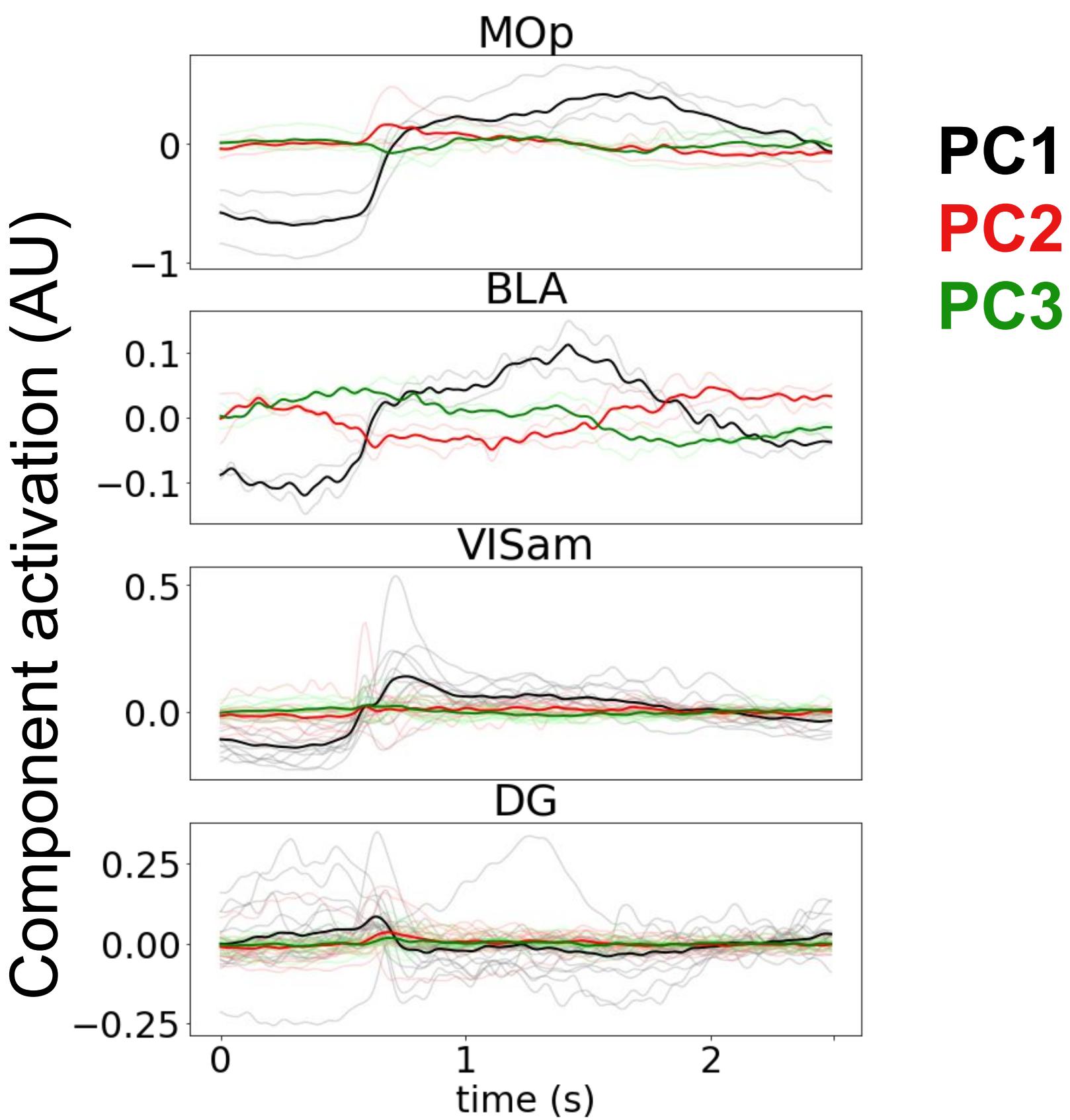
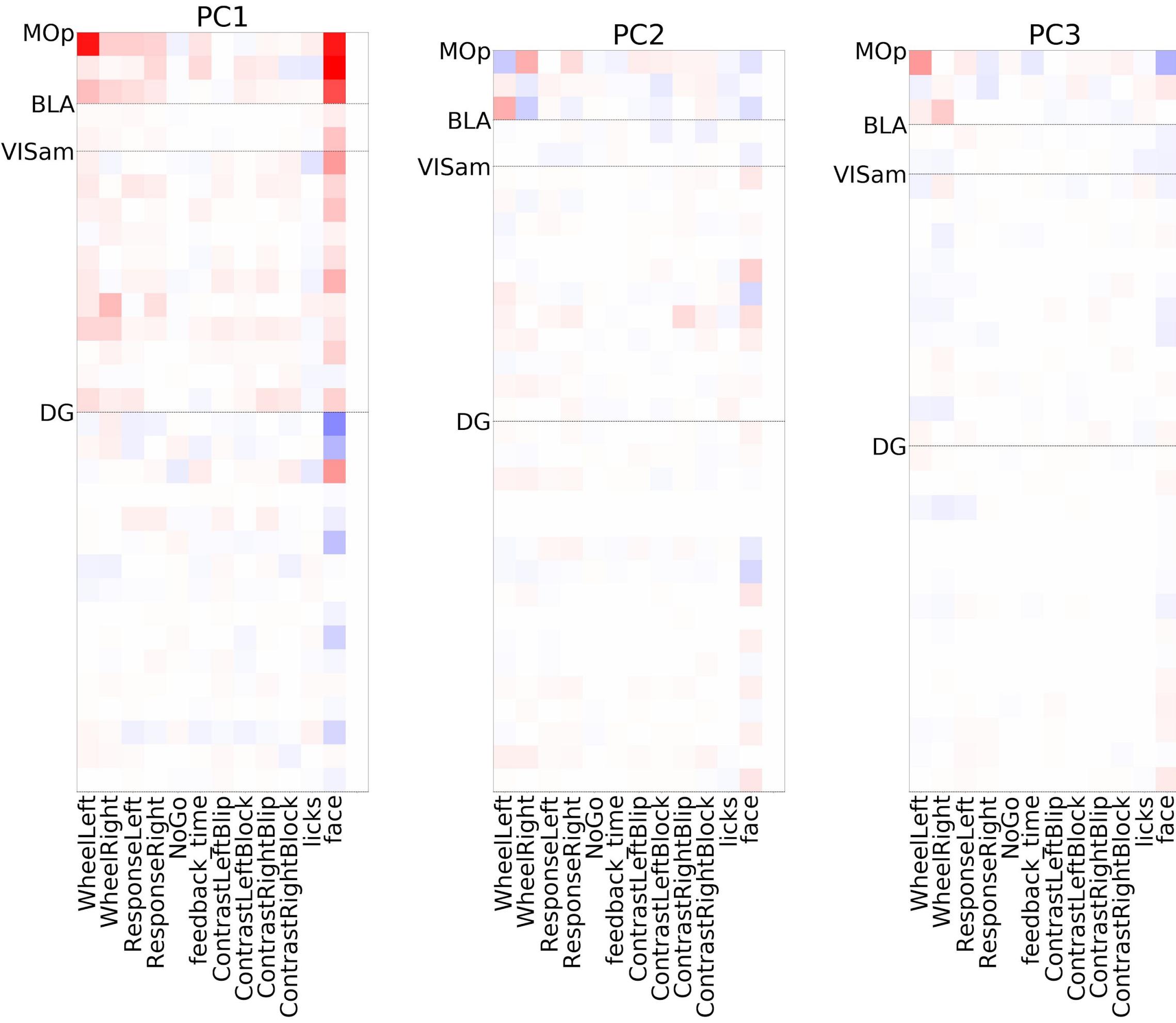
Time Course of activity projected onto PCs



PC1 PC2 PC3

Can we relate the latent variables identified in the experimentally recorded neural population by PCA to observable behavior (e.g. wheel speed, stimulus, task choice)?

Regress task variables against projections onto basis vectors



Conclusions

- Dimensionality increases in task vs. passive
- For several brain areas the top PCs are correlated with task/behavioral variables
- Variables correlated with PCs are mainly motor

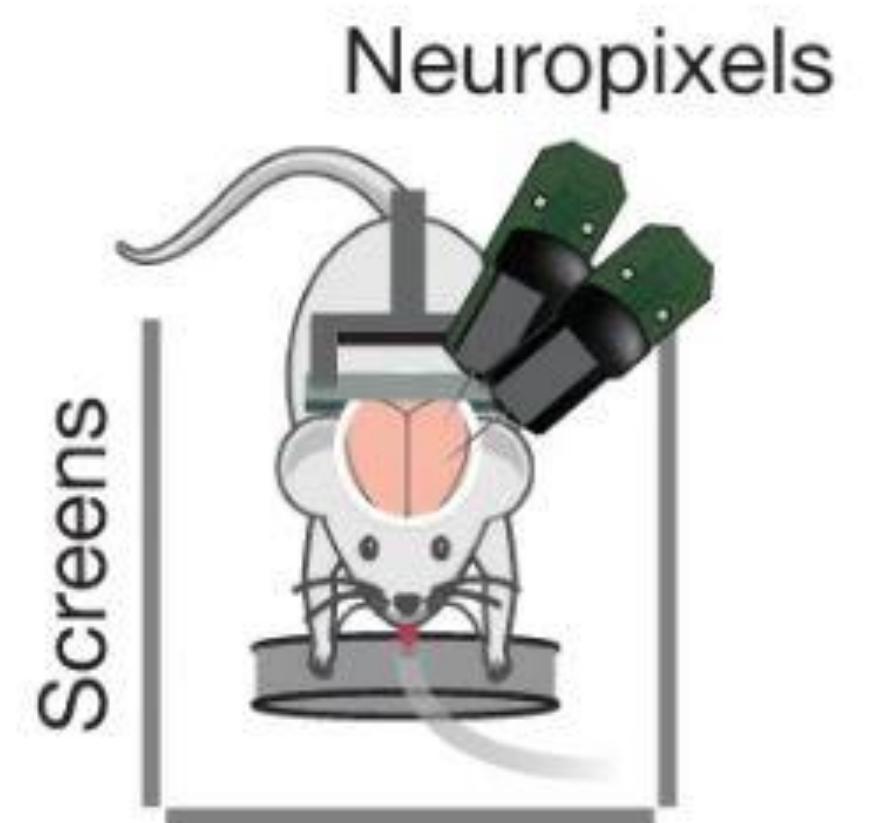
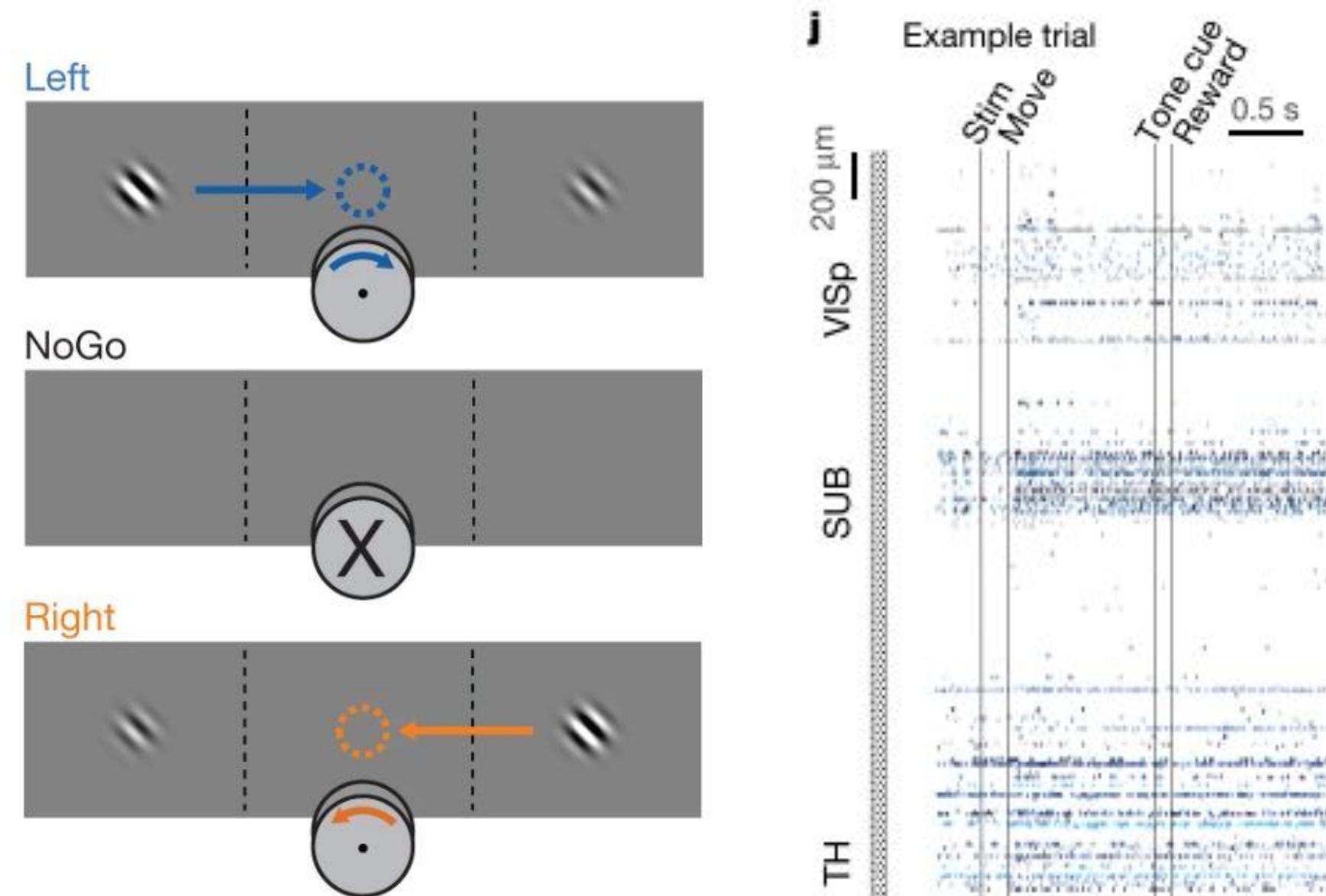
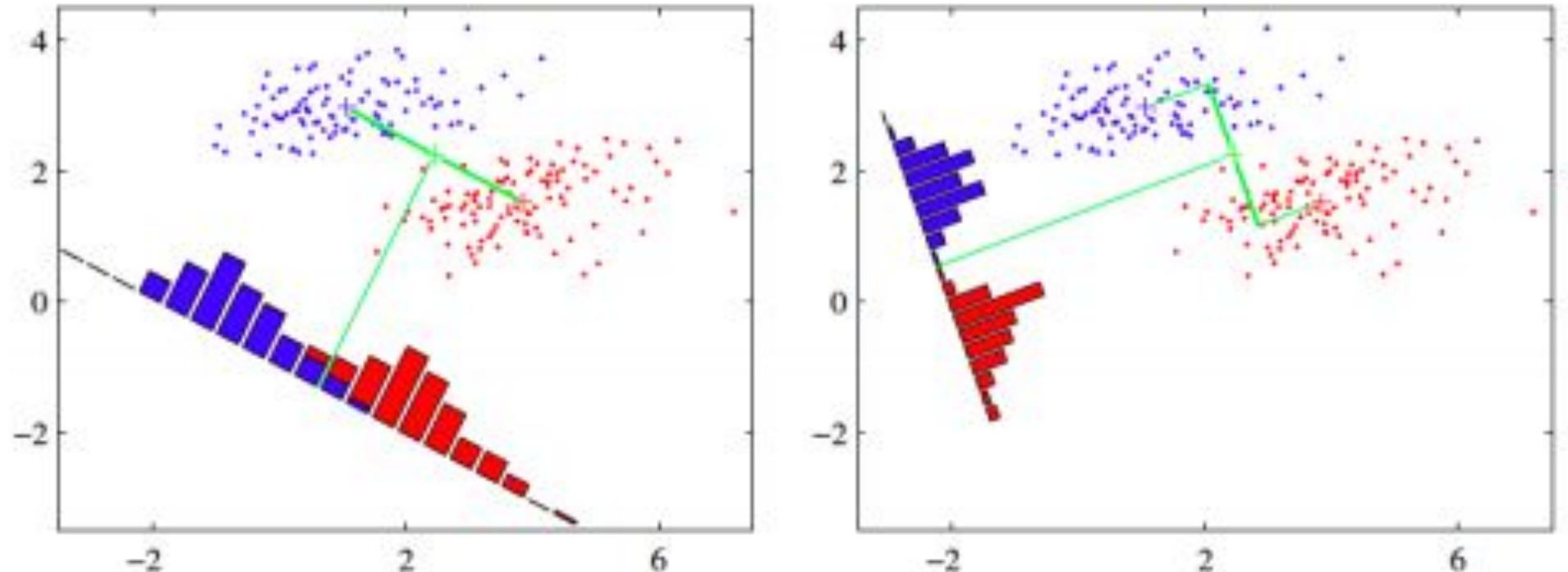
Brain-wide recording in visual behaviour

- Neuropixels probes
- 30,000 neurons - 42 brain regions
- 10 mice - 39 sessions - 10,000 Trials

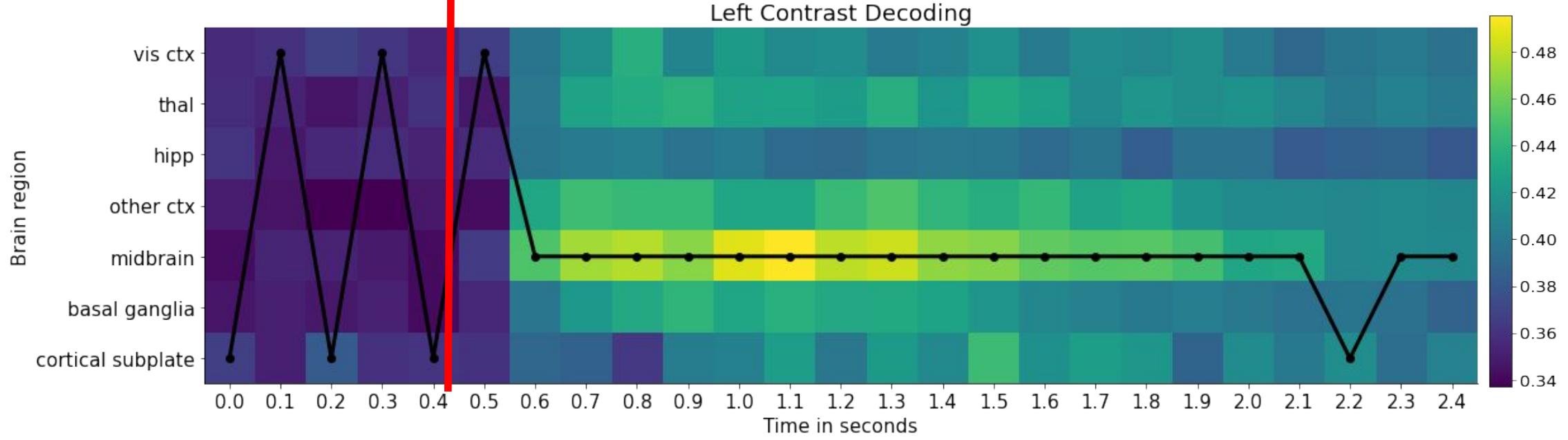
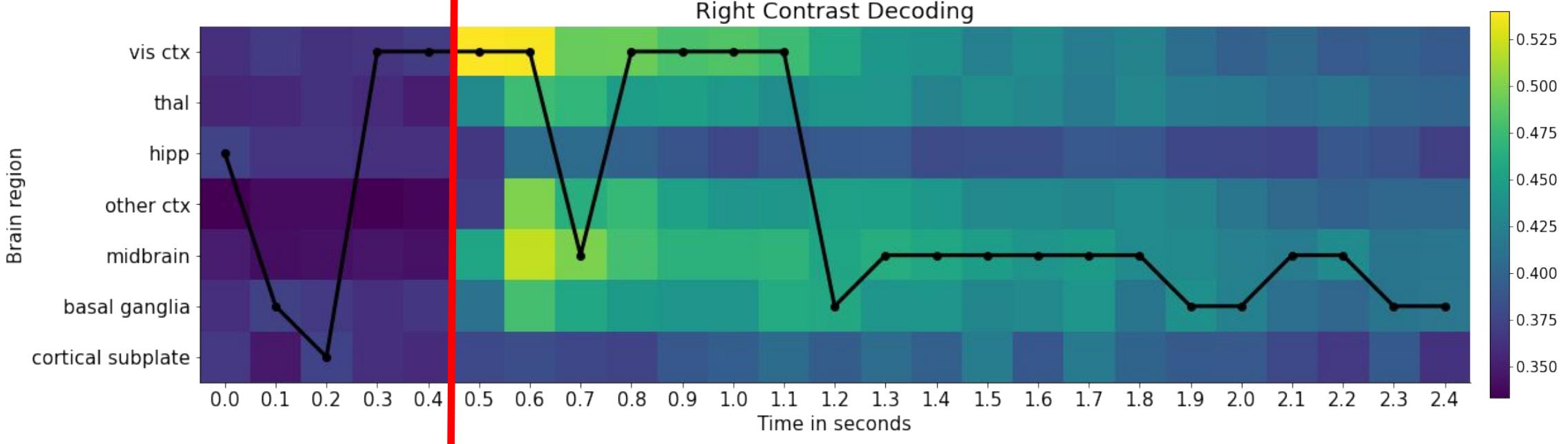
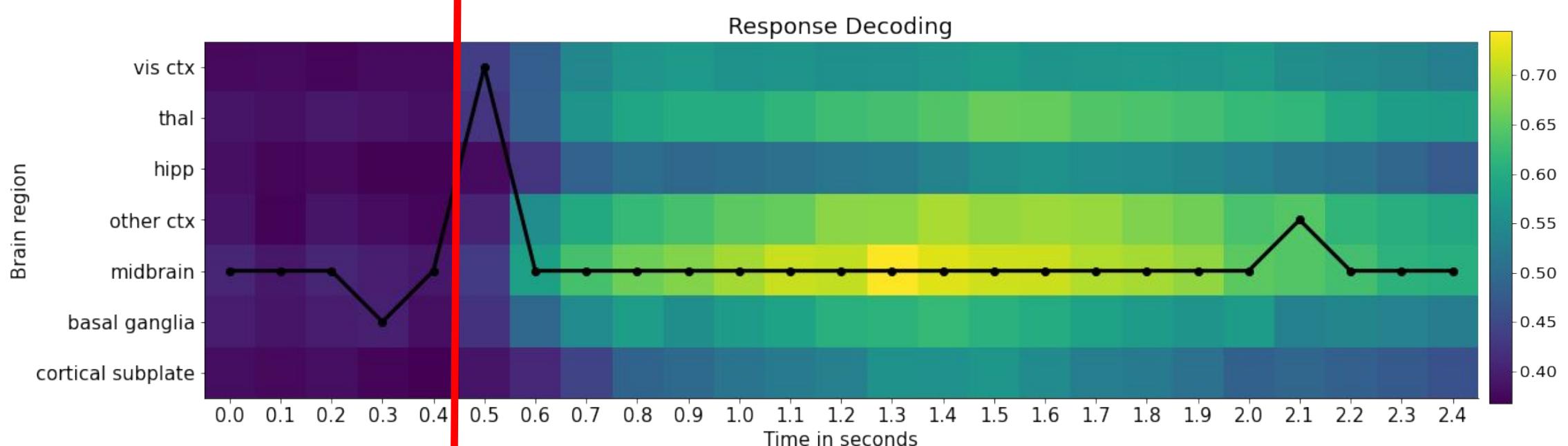
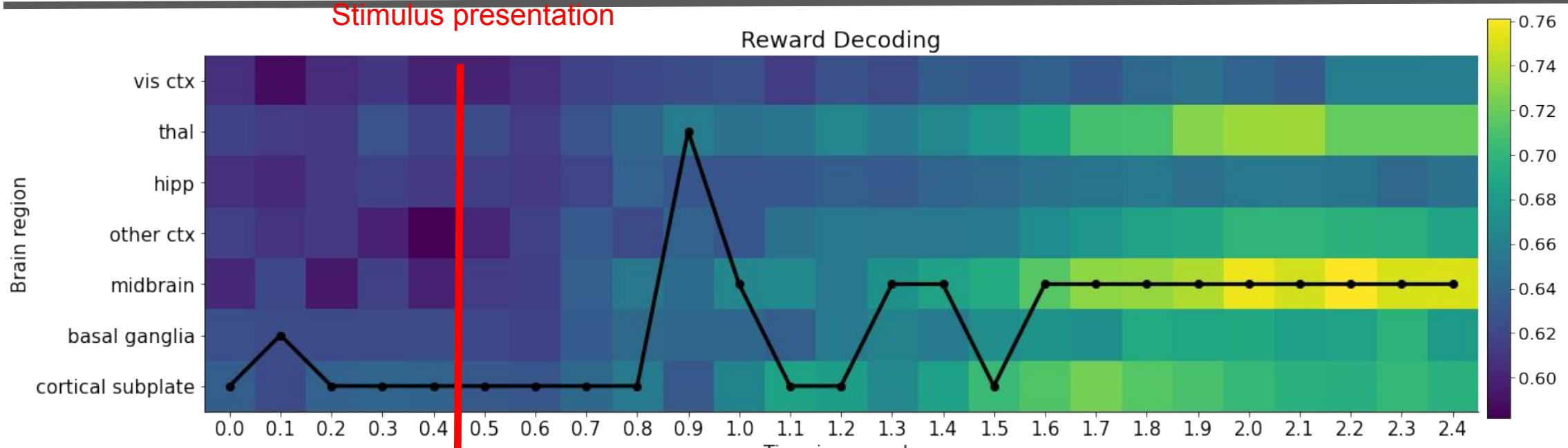
Question:

- Investigate neural representations that encode sensory stimuli, register reward, and give rise to behavioral responses. We aim to uncover the brain regions mostly encoding these representations and explore their temporal evolution
- Hypotheses: Modular Vs Distributed representations?

Technique: Linear Discriminant Analysis (LDA)

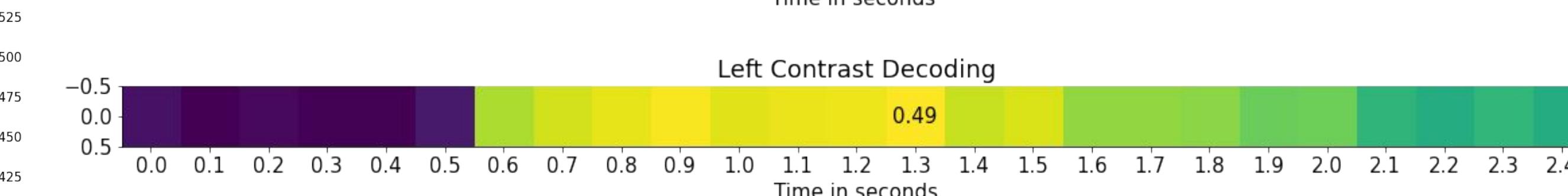
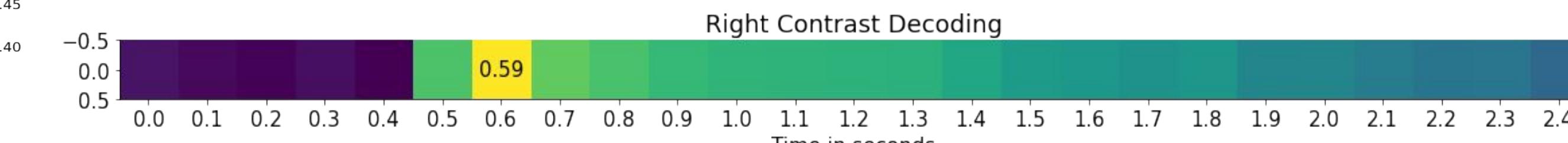
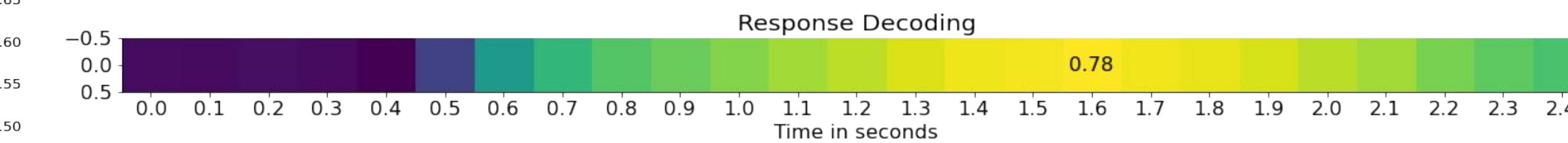


[Steinmetz et., al 2019](#)

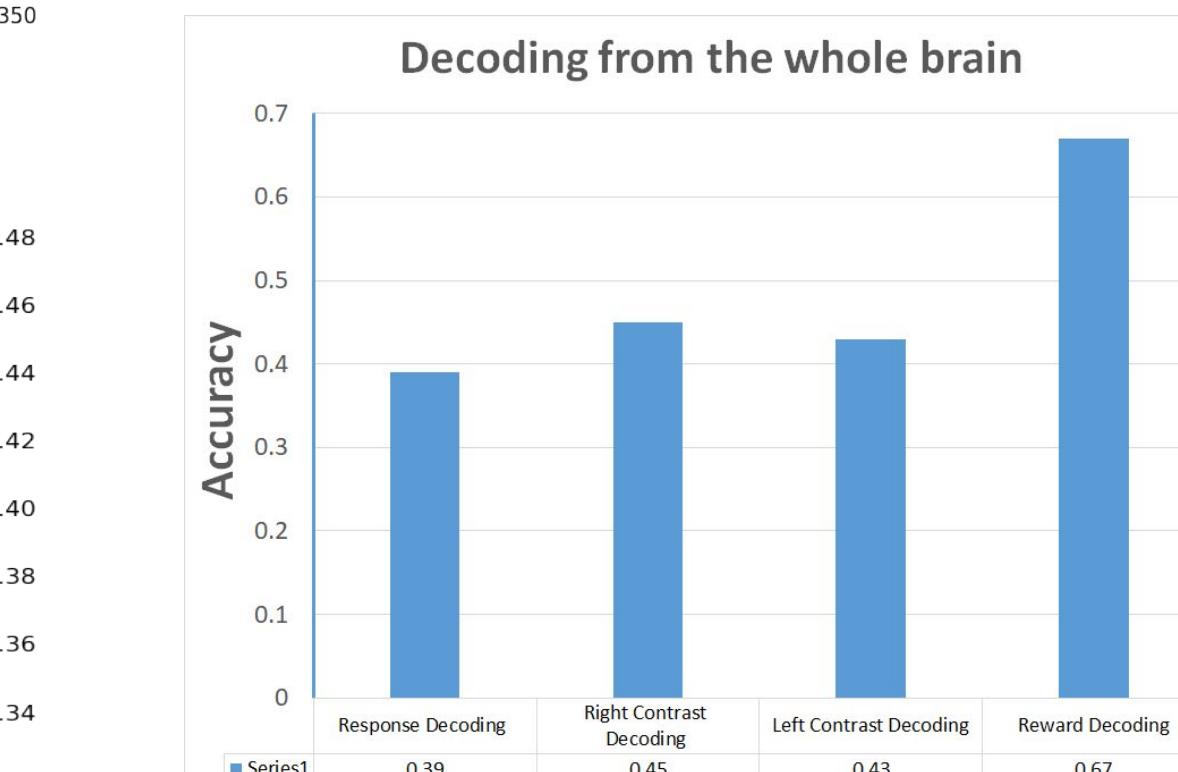


Brain region specific decoding

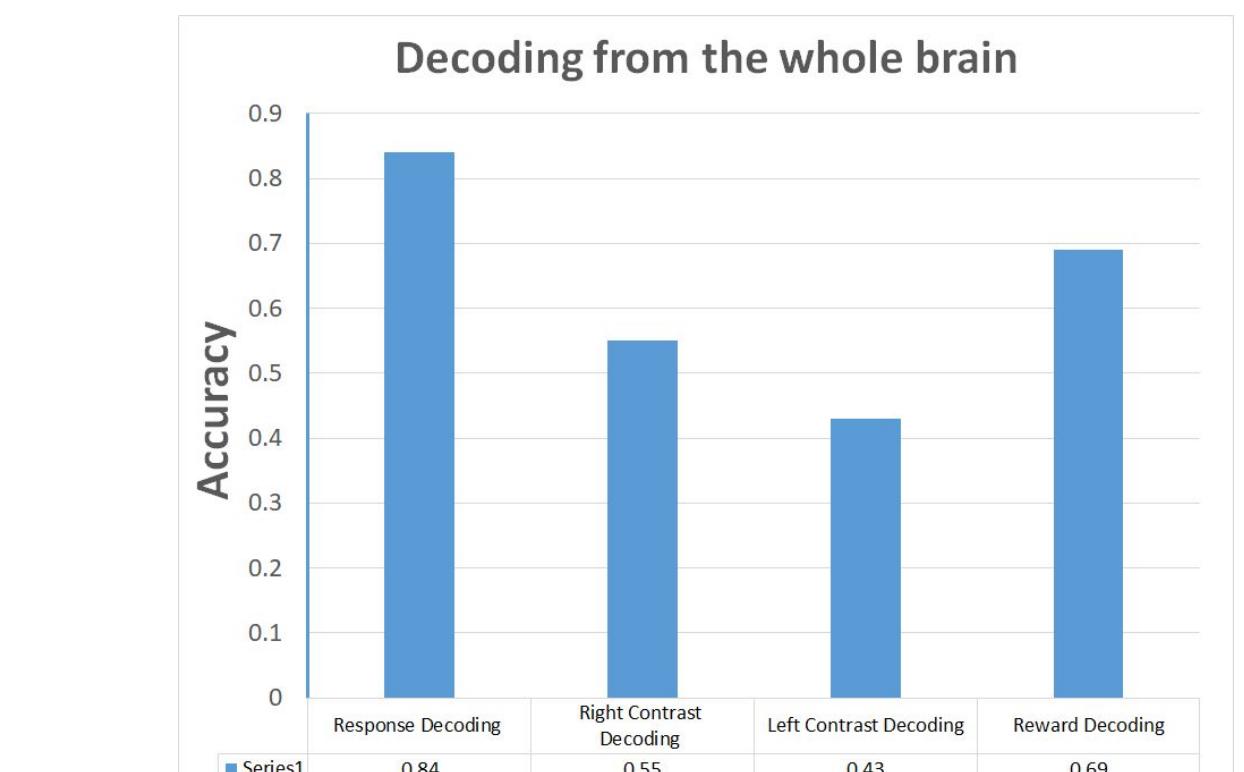
Whole brain decoding



Time points as Features ↓



Neurons firing rates as Features ↓

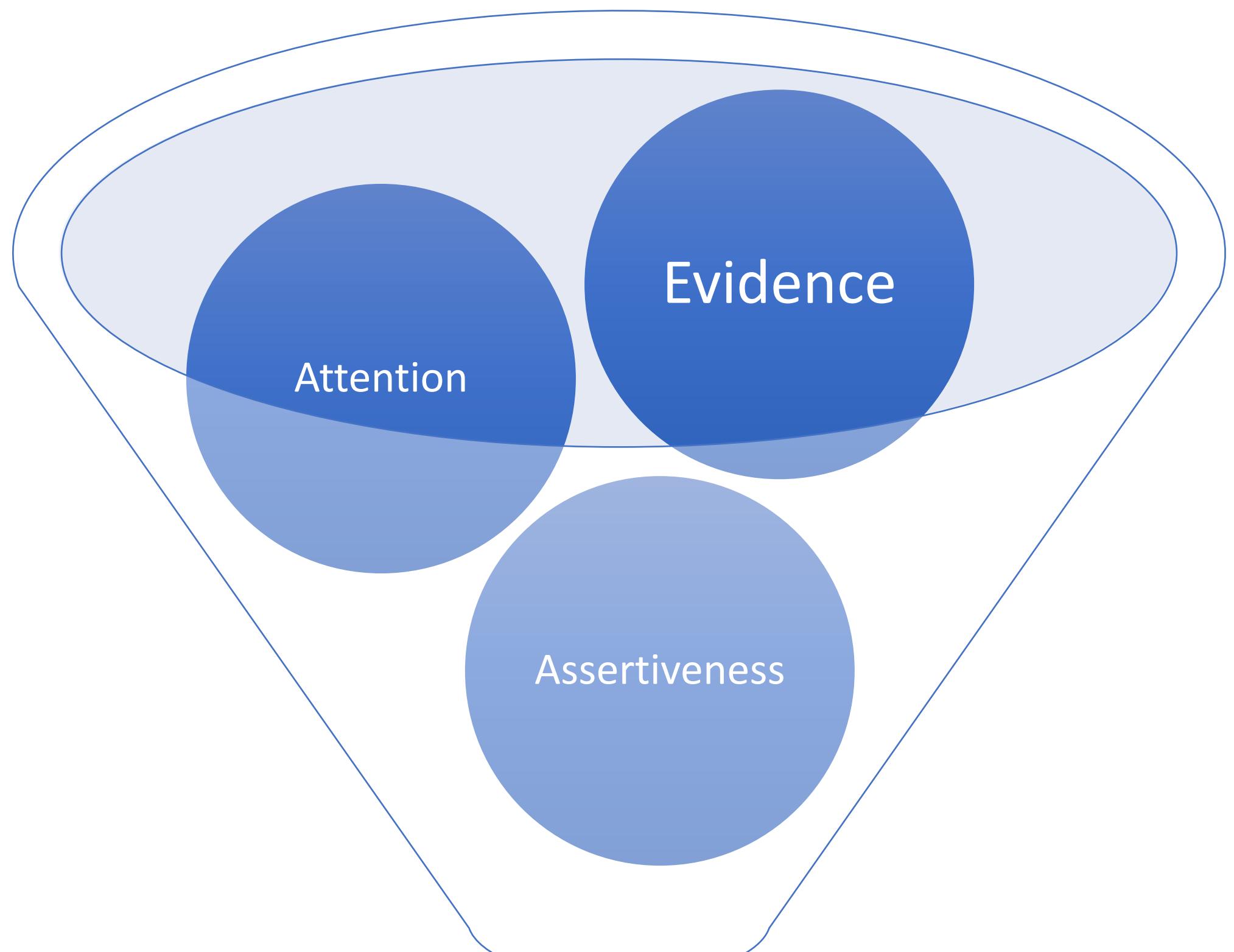


Conclusions :

1. Right stimuli were best decoded from the visual cortices right after stimulus presentation, and then from the midbrain in later time points, whereas left stimuli were merely decoded from the midbrain (probes are inserted in the left hemisphere)
2. Reward was maximally decoded from the midbrain 2 seconds after the beginning of the trial (feedback time was on average around 1.6 seconds), but also from the thalamus at similar time points.
3. Response decoding was more widespread across brain regions and time, which reflects the slow nature of action in comparison to perception.
4. Right contrast and response decoding showed substantial improvement when data was pooled from the whole brain in comparison to the highest decoding brain area which suggest a more distributed neural representation of action and perception than a modular system.
5. How the data was pooled was detrimental for the performance of the decoder. Averaging the neuronal responses and using time points as features led to a significant drop in the accuracy of response decoding to almost chance level which shows that timing is an important factor for these distributed neural representation.

Experiences:

1. LDA with shrinkage regularization proved to be fast and reliable decoder for neural activity and serves as a strong baseline (on par with a feed-forward fully-connected neural network and better than logistic regression).
2. [PHATE](#) didn't provide meaningful clusters when we tried to use it to find distinct patterns of neural activity among different brain regions. The problem could be our choice of features and needs further investigations.
3. We tried to use [HDDM](#) to model the animals' decision making based on the neural activity but we faced some technical difficulties.



Hesitant mouse: capturing confidence in mouse behaviour

Moshe Roseman

&

Noham Wolpe

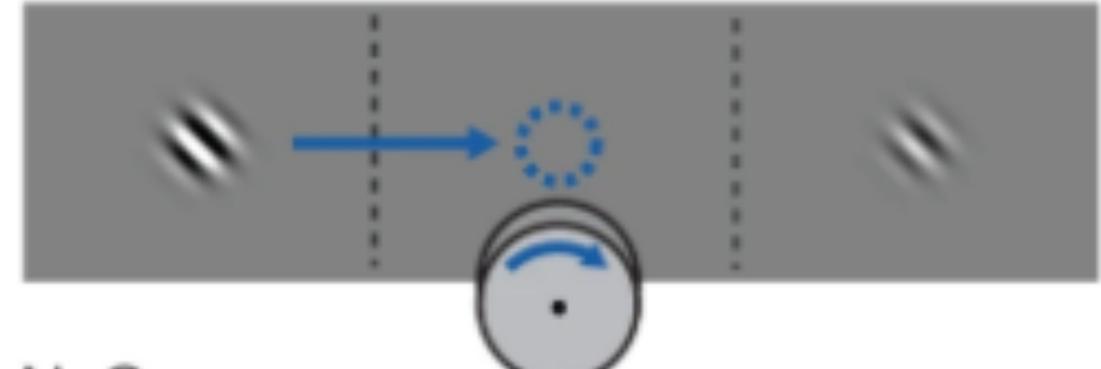
Mentor: Jacob Yates

Hesitant mouse

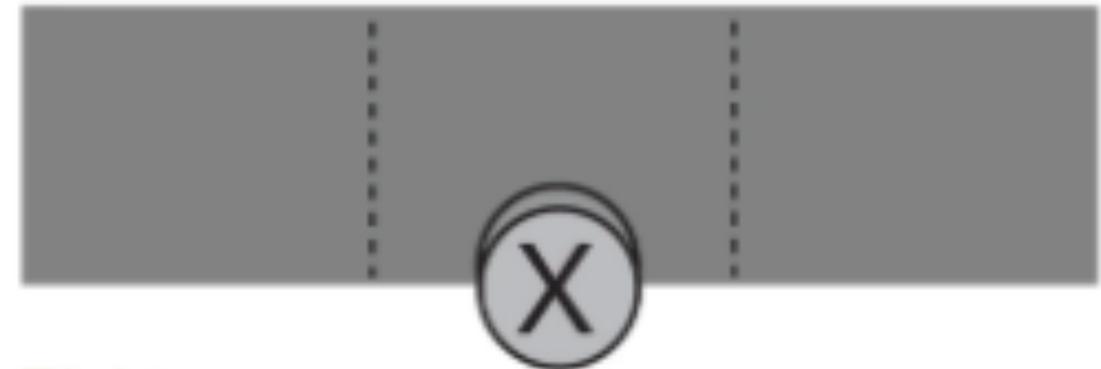
Neuropixels



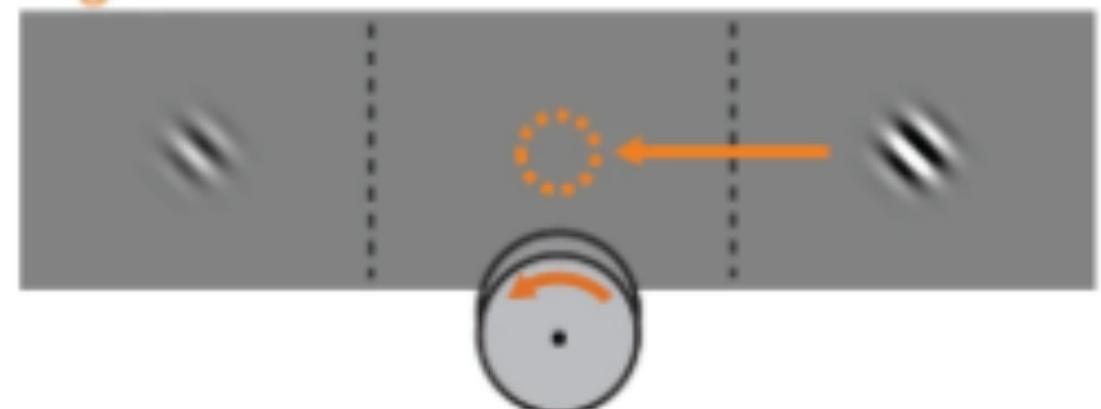
Left



NoGo

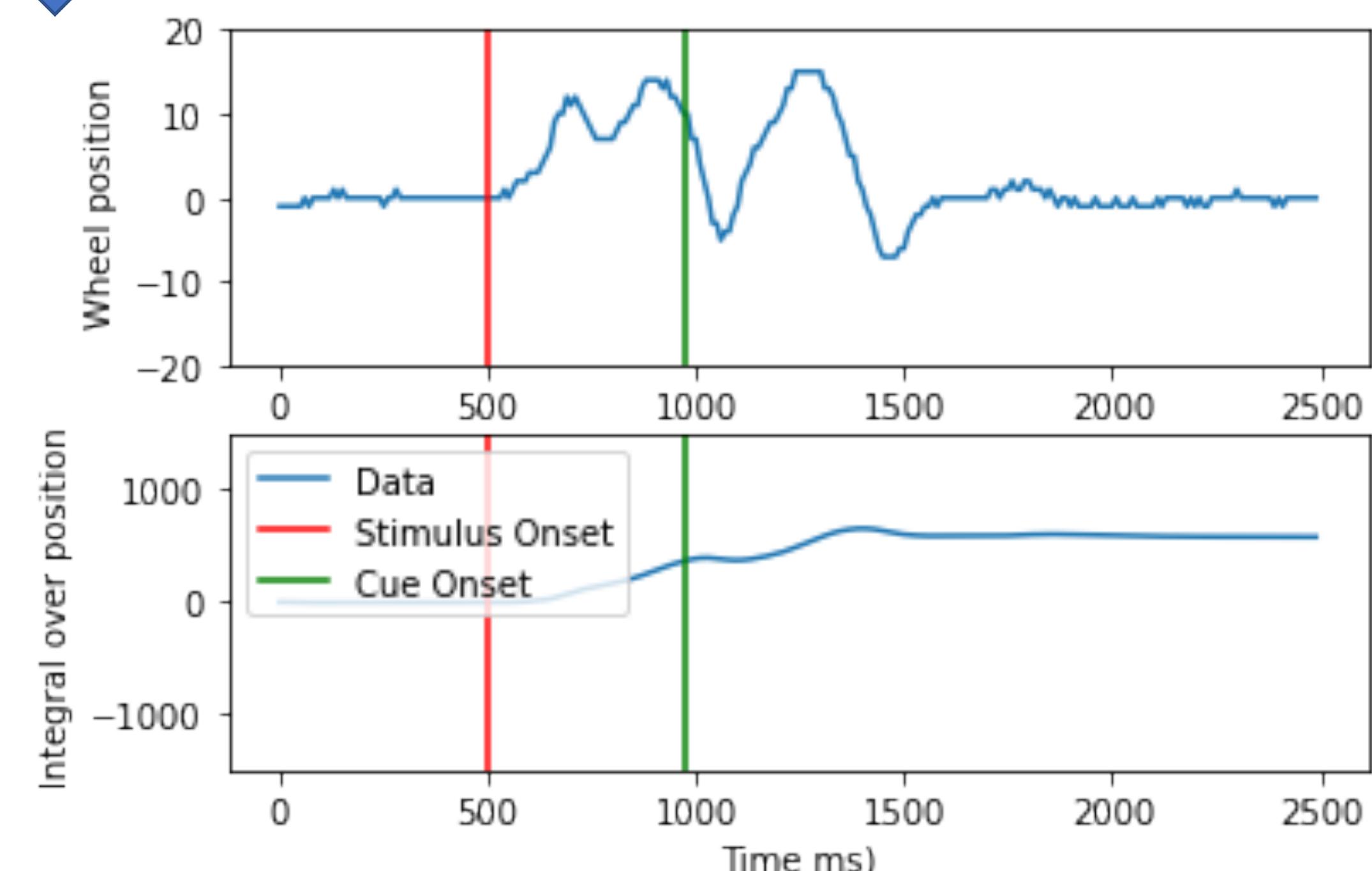
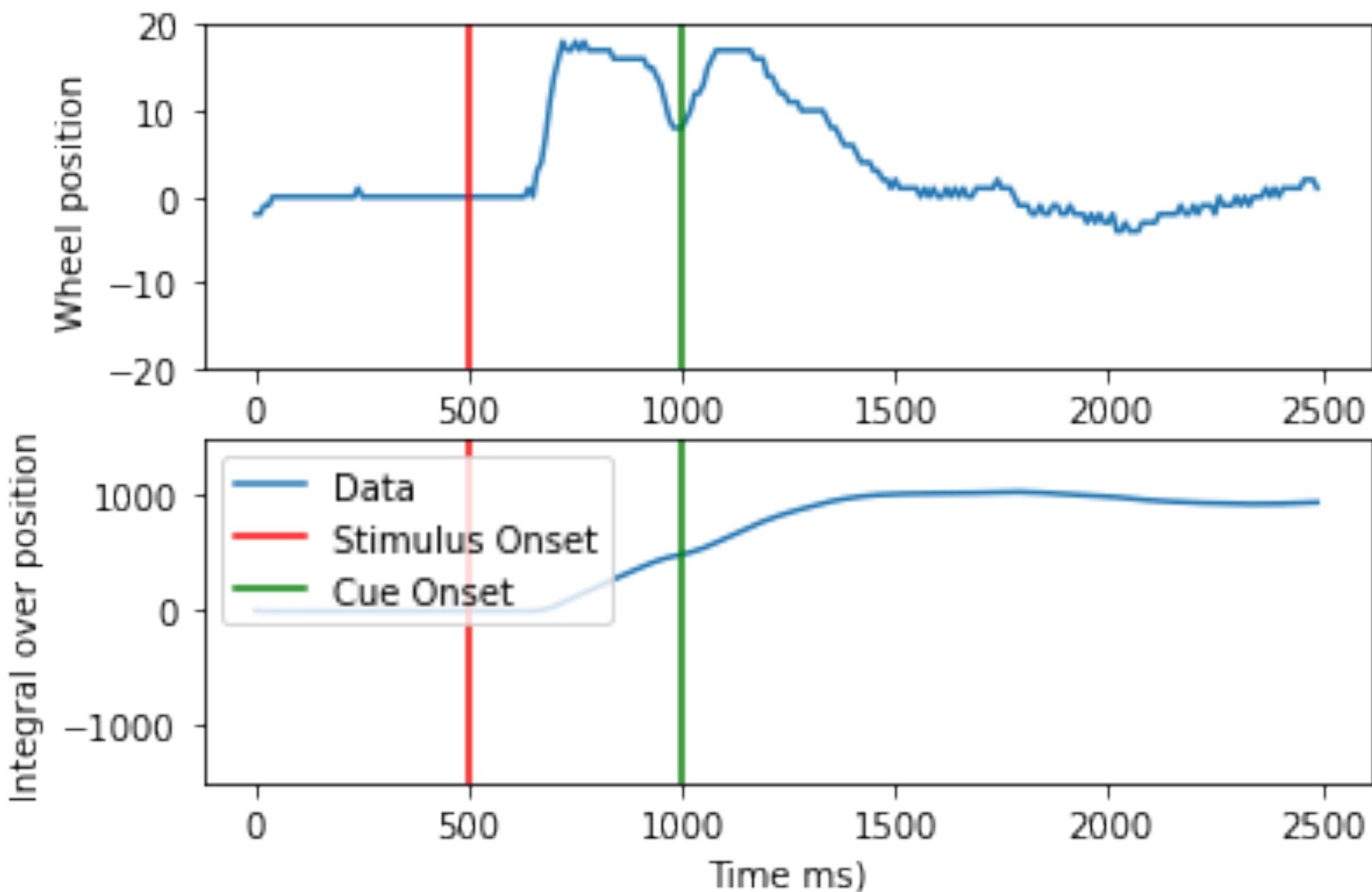


Right

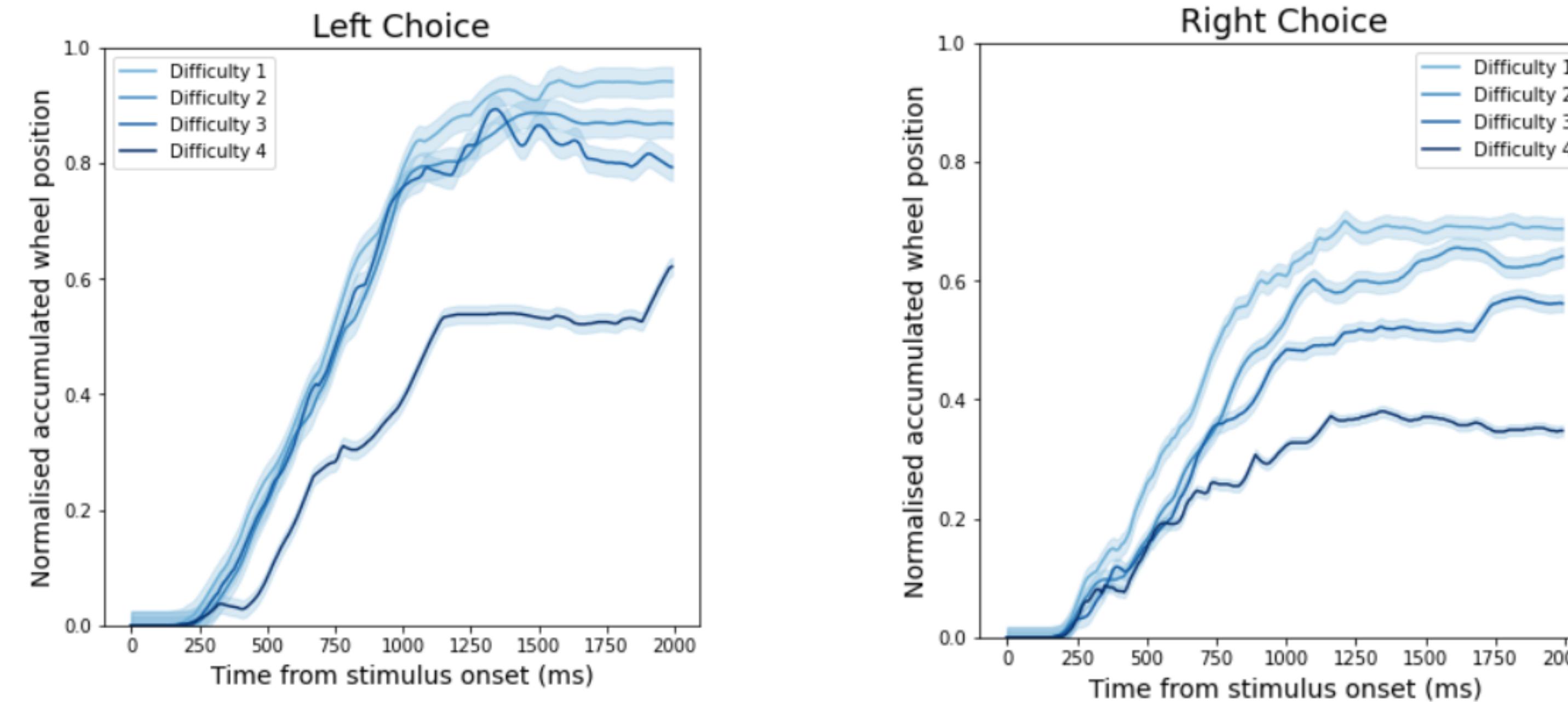
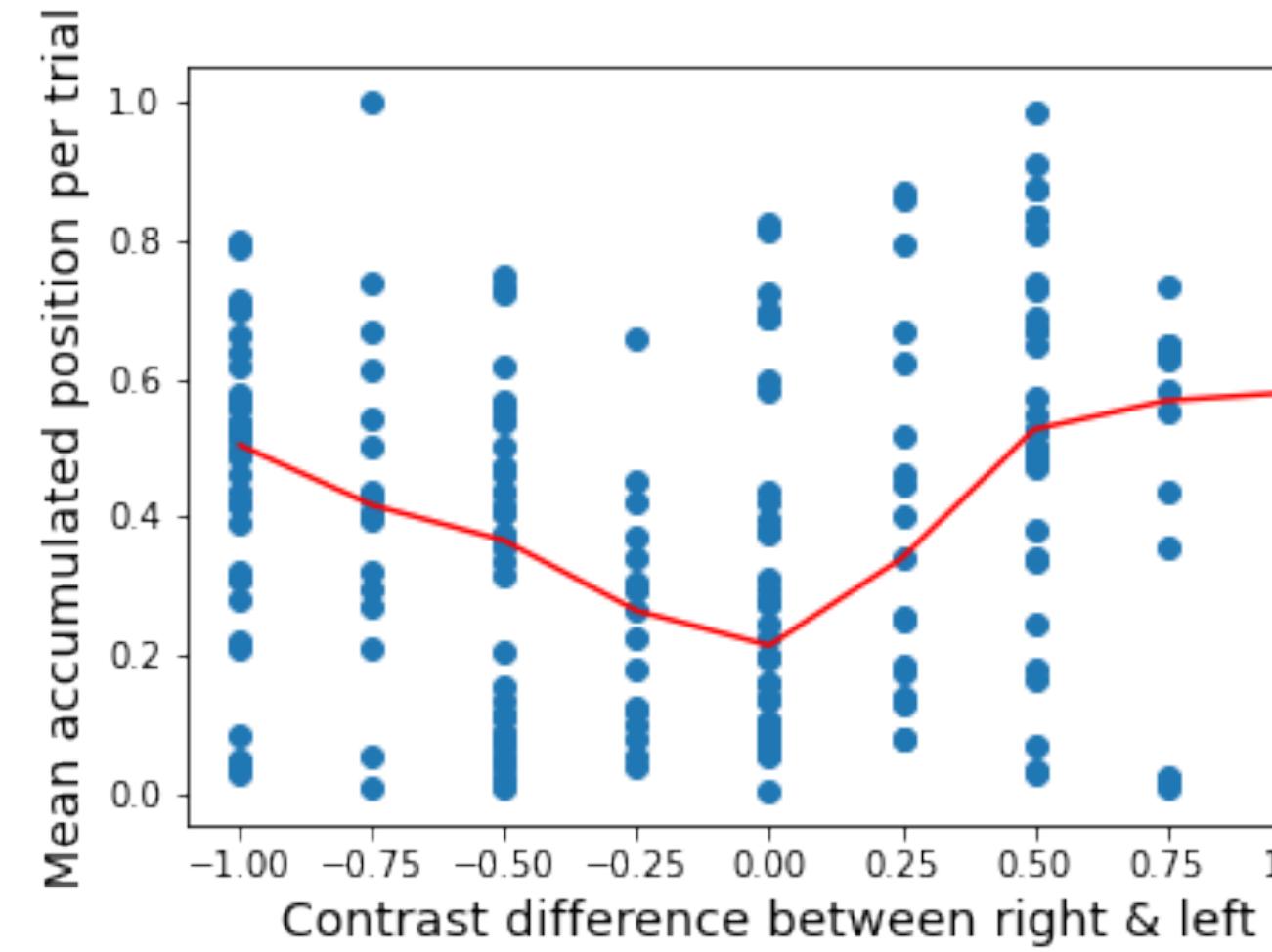


Contrast difference = 1

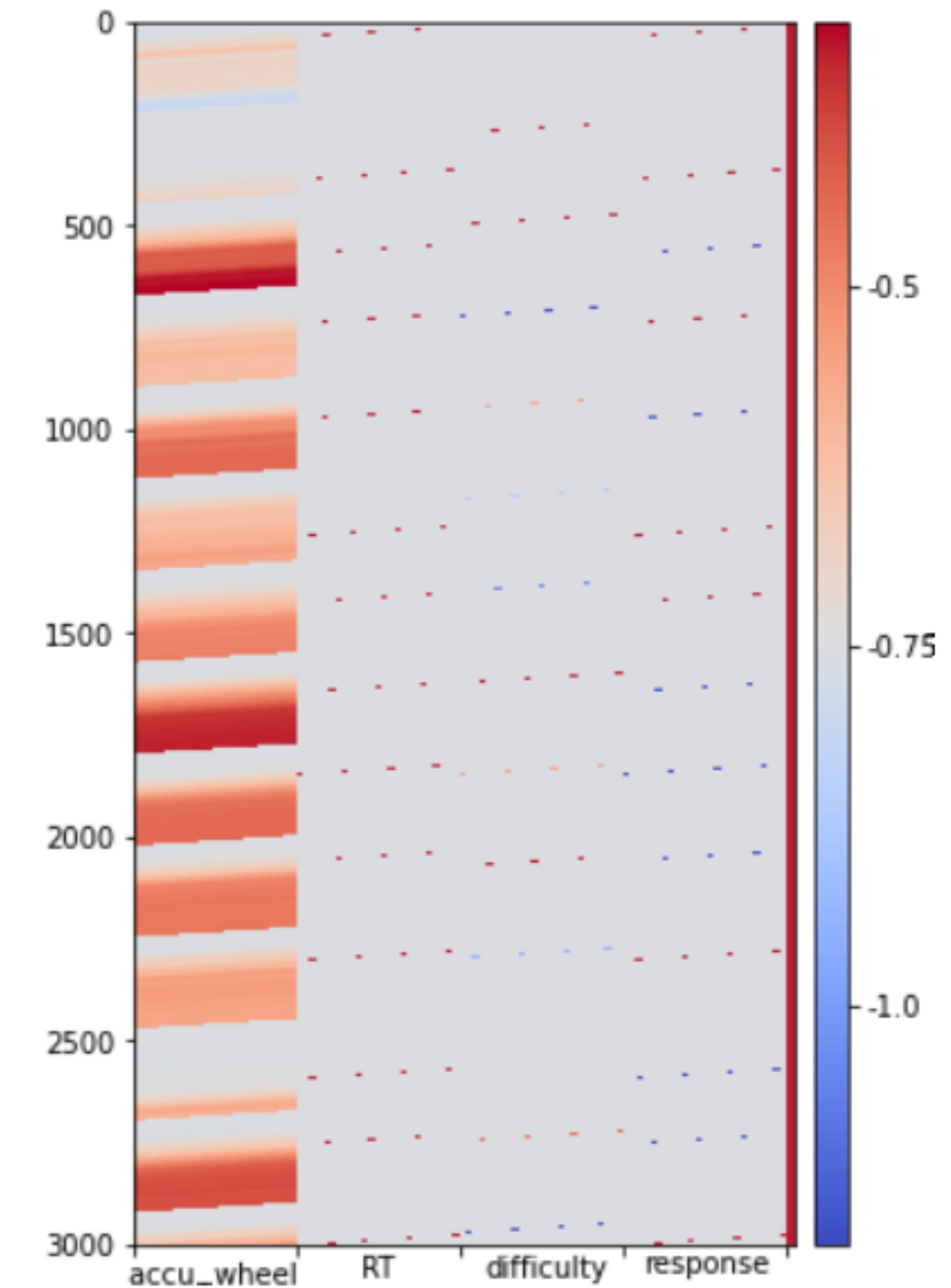
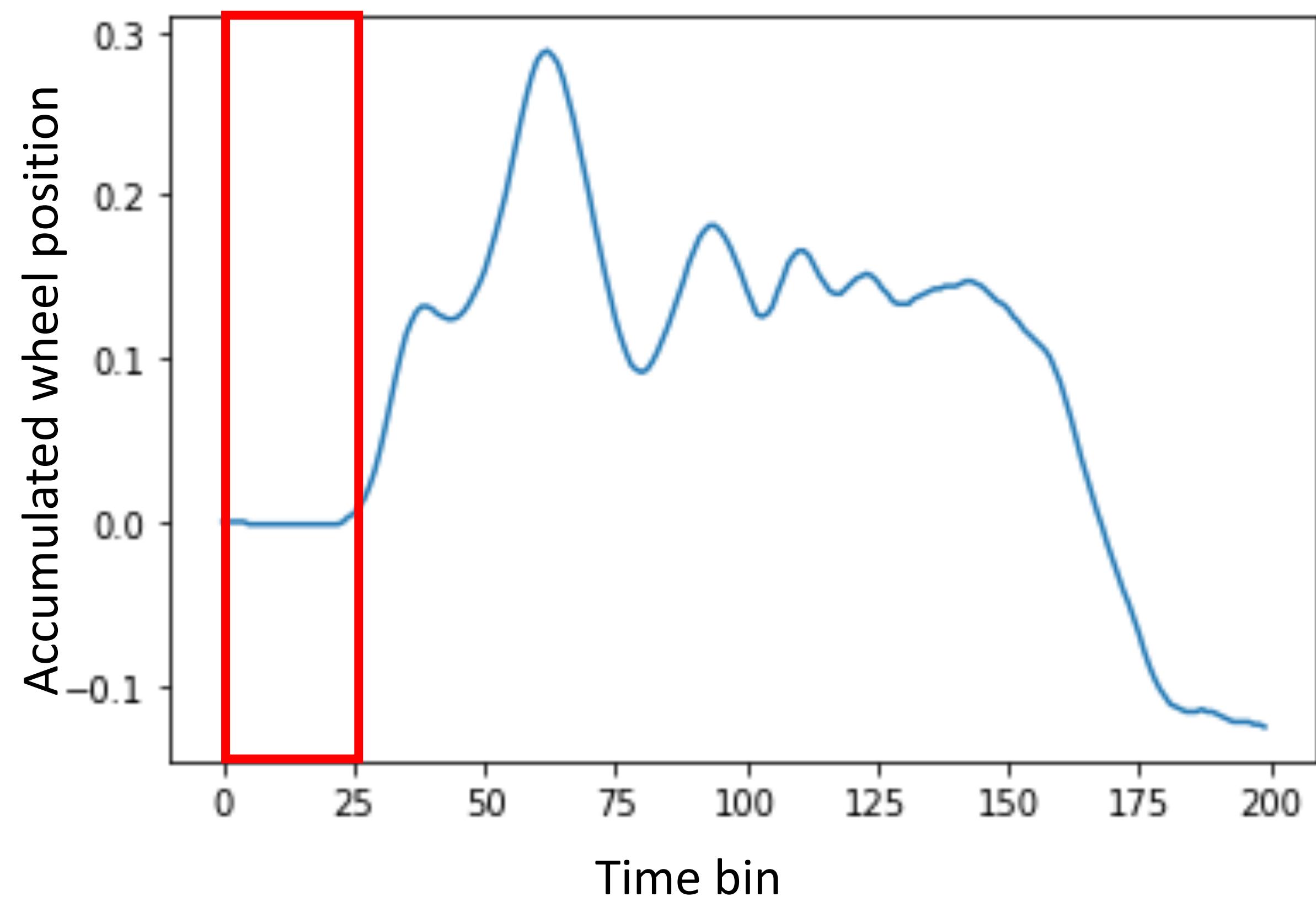
0.25



Behavioural data summary

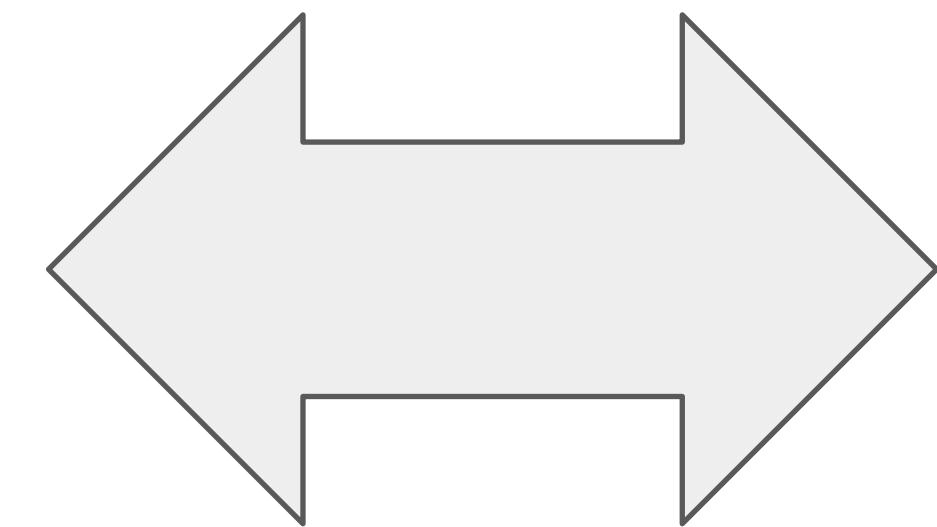


Linear-Gaussian GLM



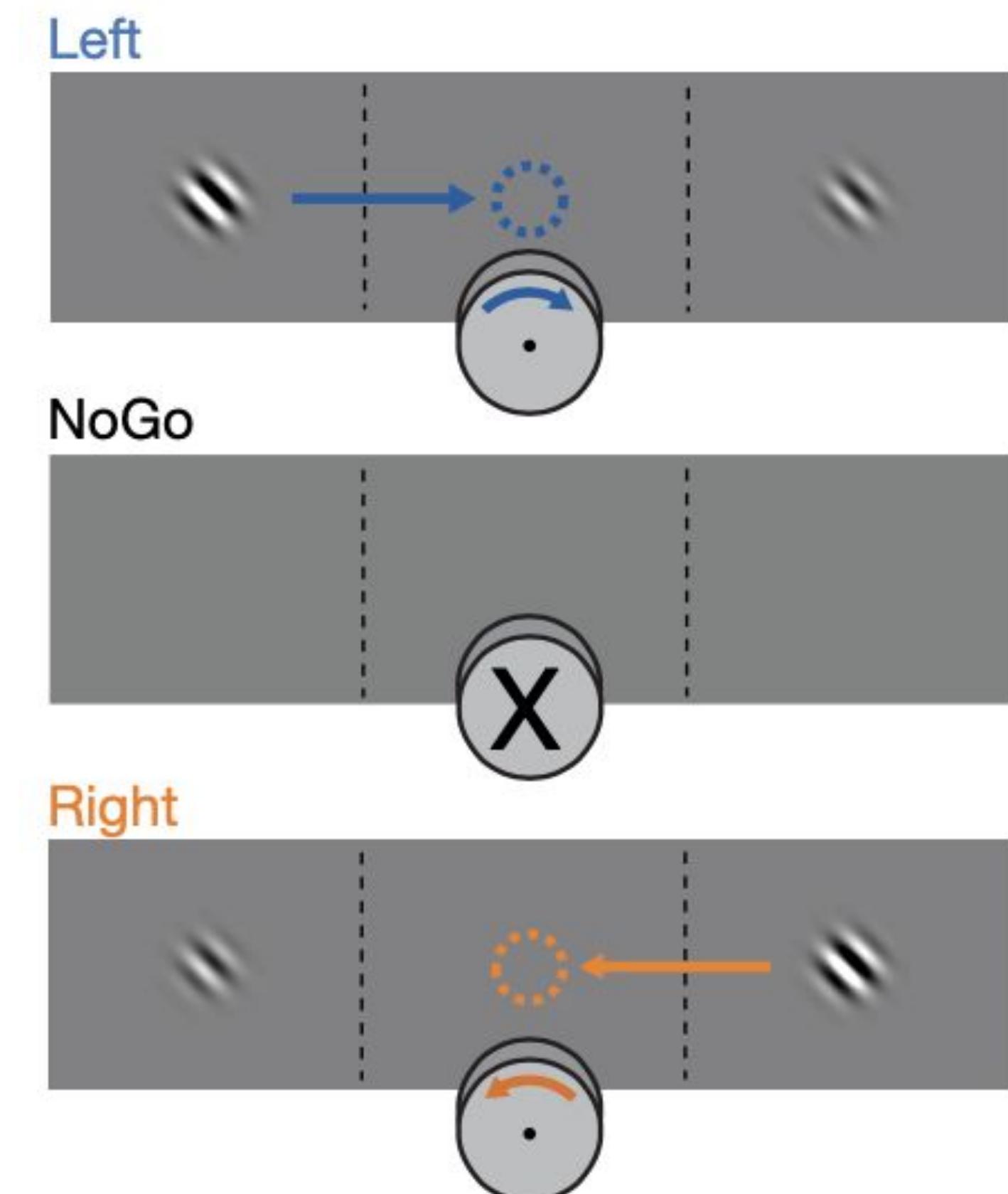
Effects of trial history on current decisions

- Animals constantly make decisions based on prior experience.
- But what aspects of prior experience are most important in decision making?
- Previous studies demonstrate that movement history, stimulus history, and reward history all can influence current decisions or movements.
- We aimed to determine which of these three variables during previous trials are predictive of the current decision.



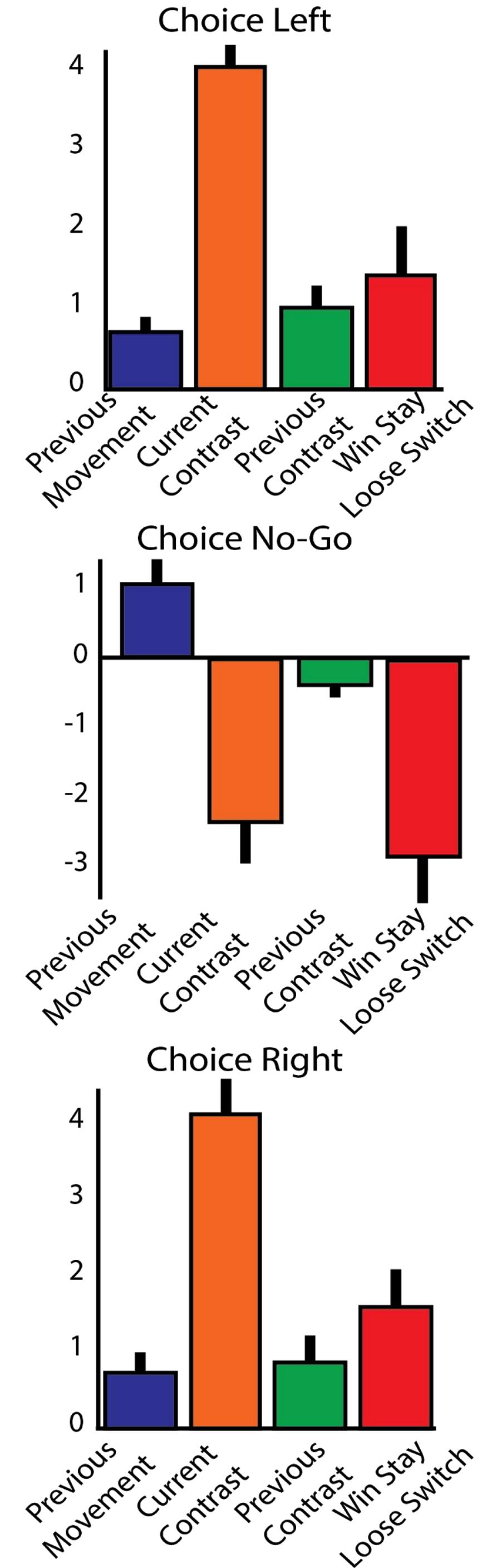
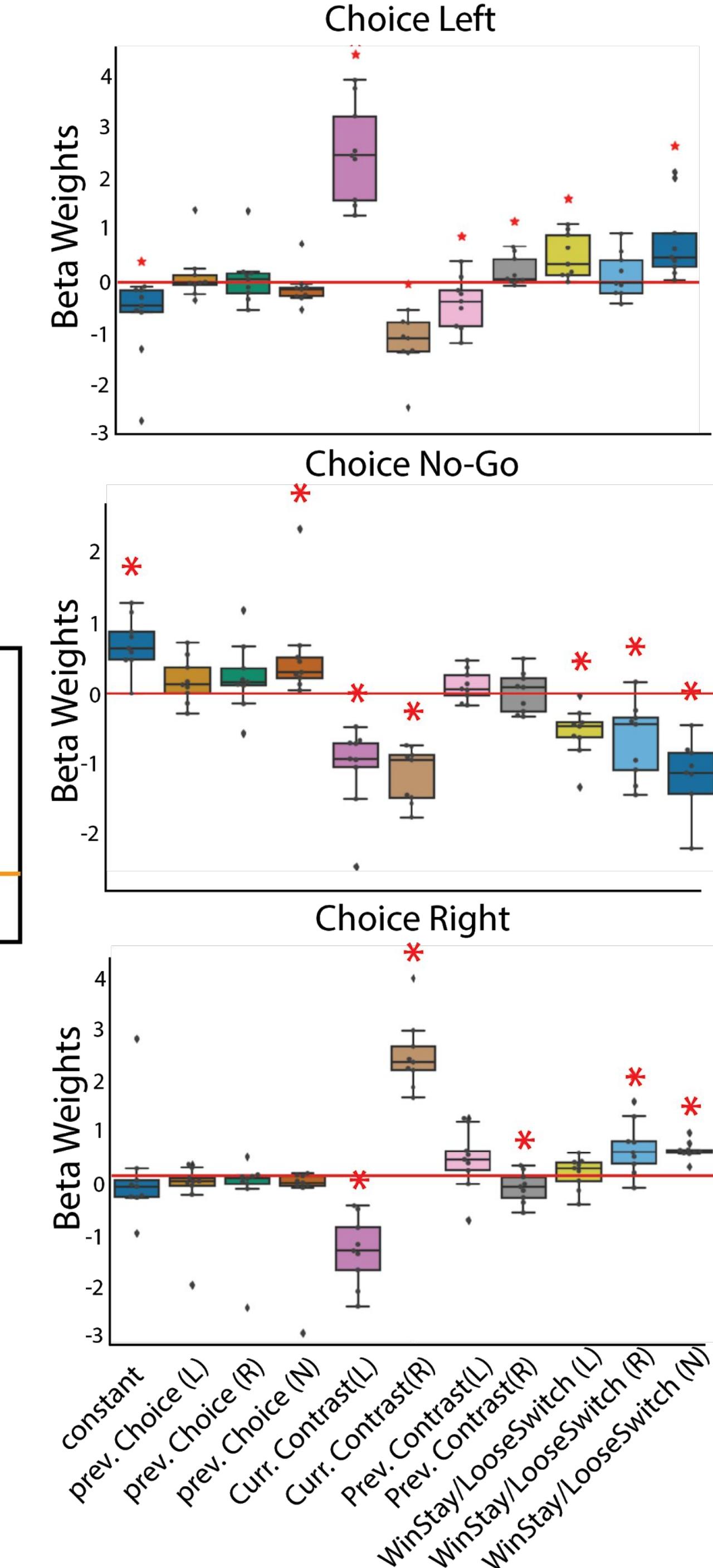
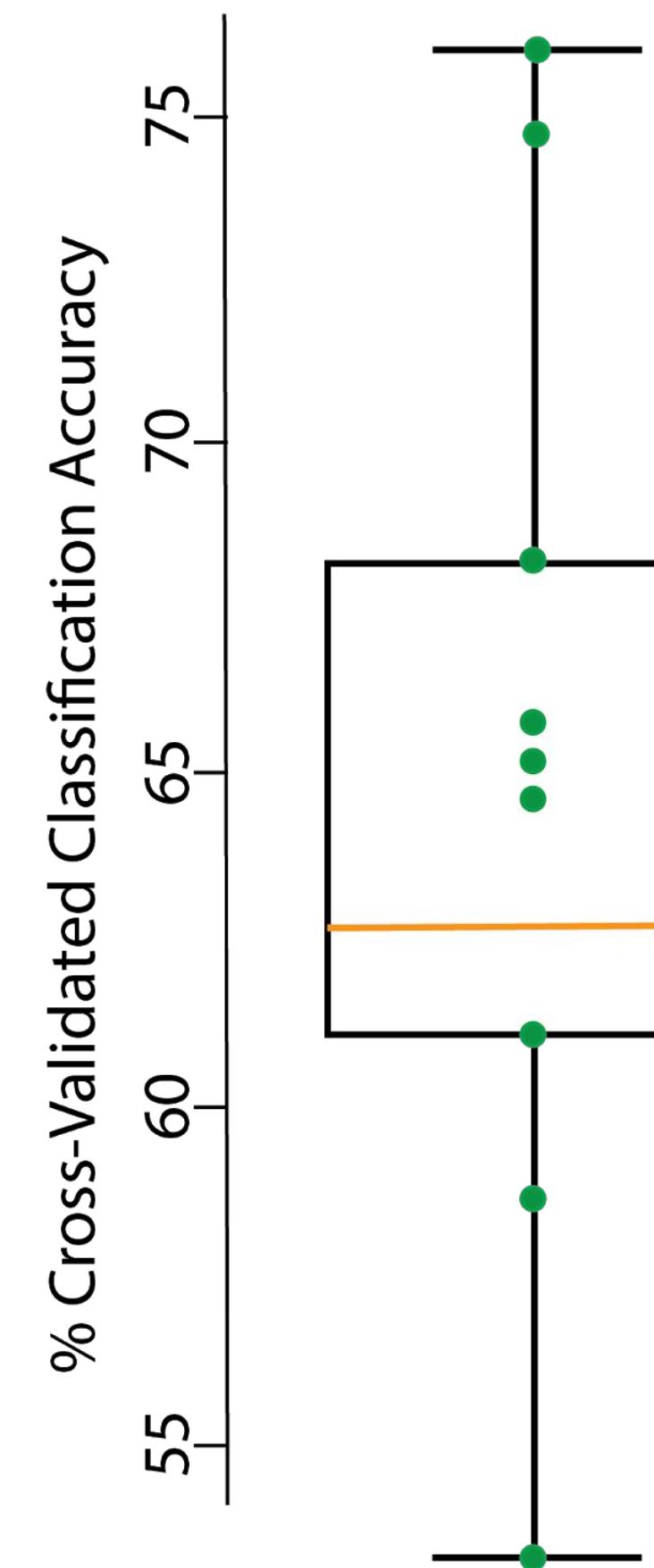
Proposed or successful analyses

- Dataset: Steinmetz et al. 2019: perceptual decision making task in mice
- Analysis: Multinomial logistic regression to predict movement direction from previous trial information
 - Regressors:
 - Current trial stimulus
 - Previous trial stimulus
 - Previous trial movement
 - Win-stay lose-shift based on the reward from the previous trial
- Model selection: Nested-cross validation, L2 Reg
- Model evaluation: permutation testing on held out data



Conclusions or experiences

- **Conclusion:** Current stimulus information was most predictive of current trial choice, but reward history was also consistently significant
- **Experience:** We found the most difficult aspect of the project to be formulating a clear scientific question. Our mentor (Ryan Low) was very helpful.



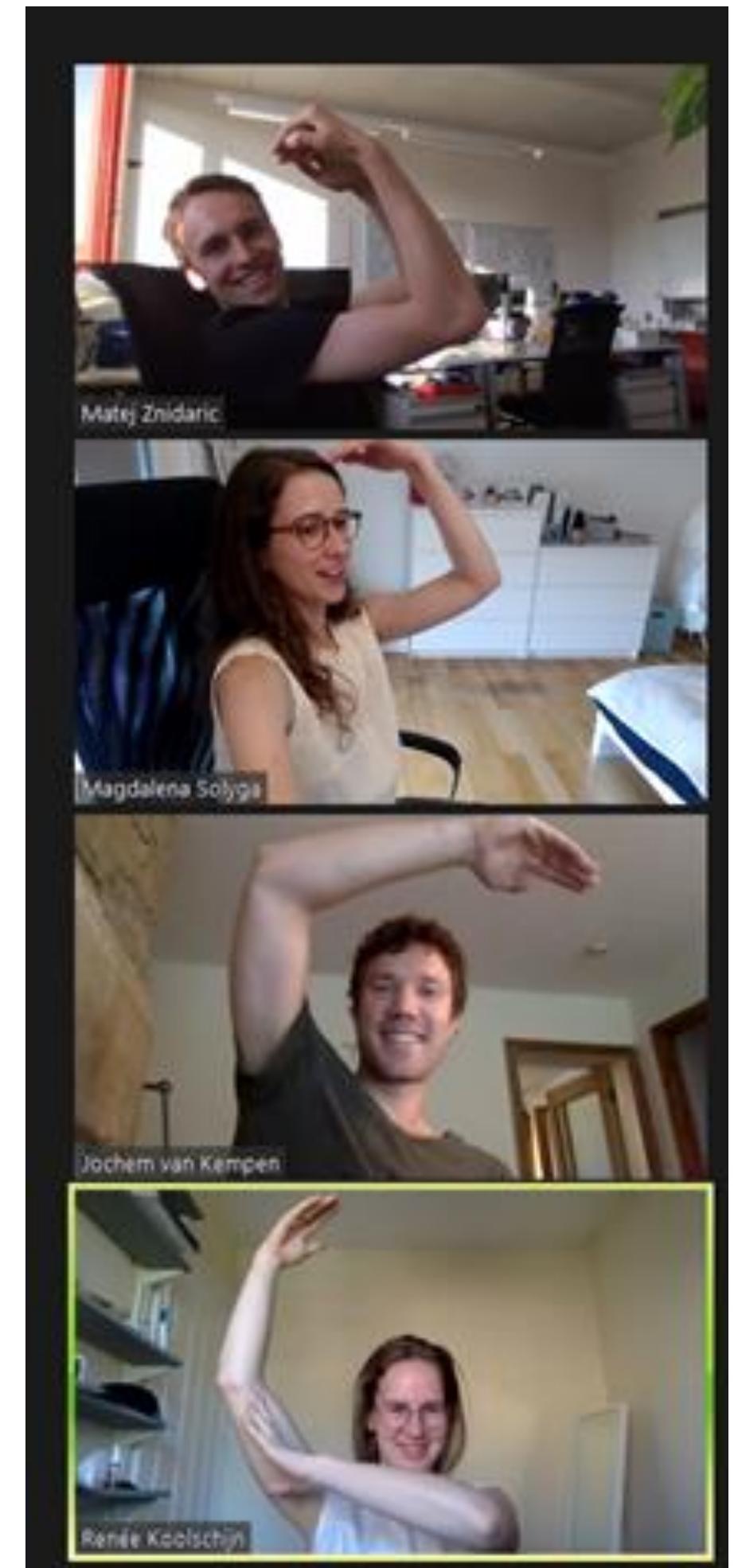
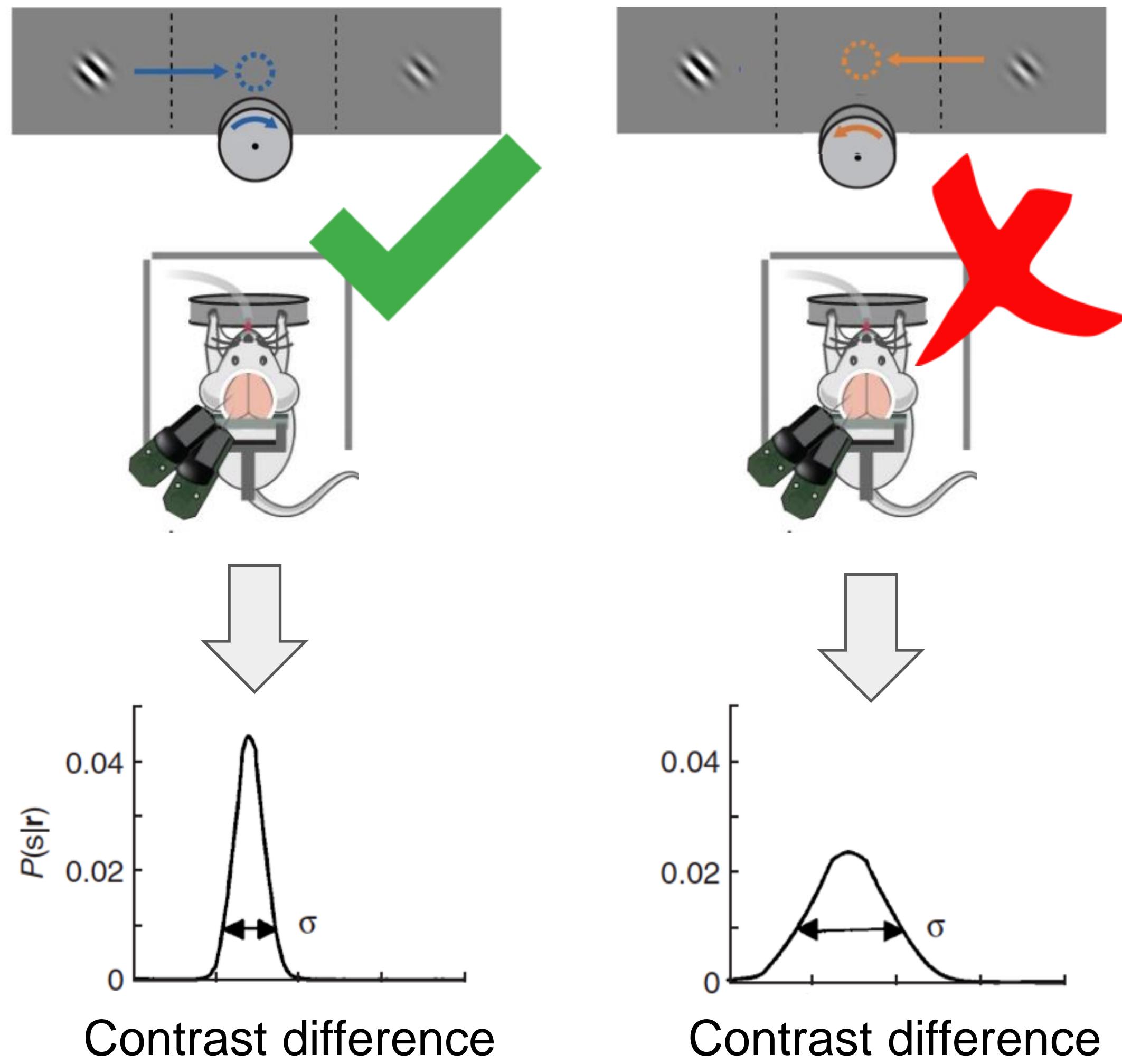
Is response variability in a neural population predictive of successful behavioural task performance?

the Bayesian crackers (BC)

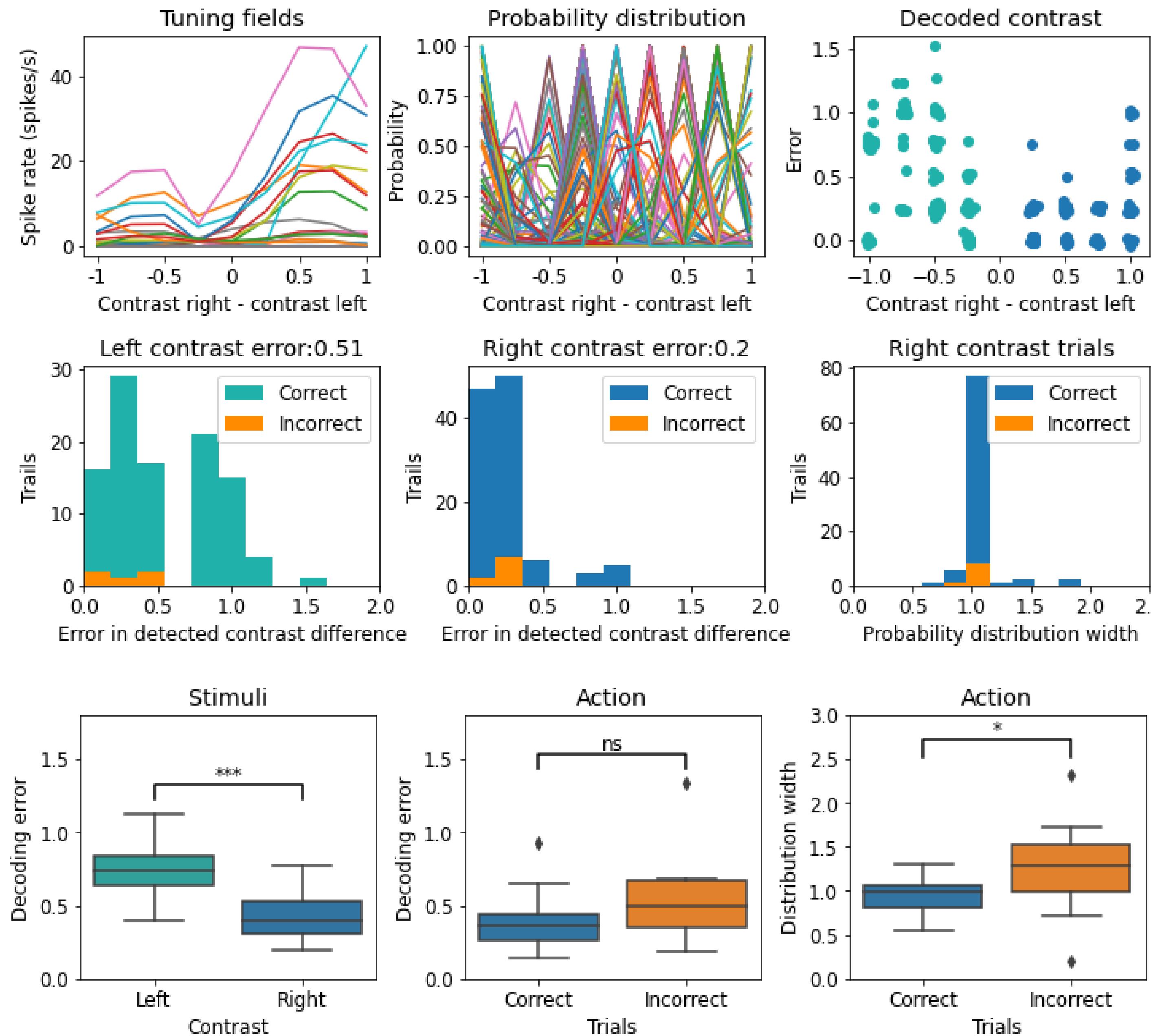
Dataset:
Steinmetz

Approach:

- Use Bayes' rule to transform tuning curves into probability distributions
- Evaluate the width of probability distribution: does it differ between correct and incorrect trials?
- How does decoding accuracy using a Bayesian framework compare to logistic regression?



Example session V1



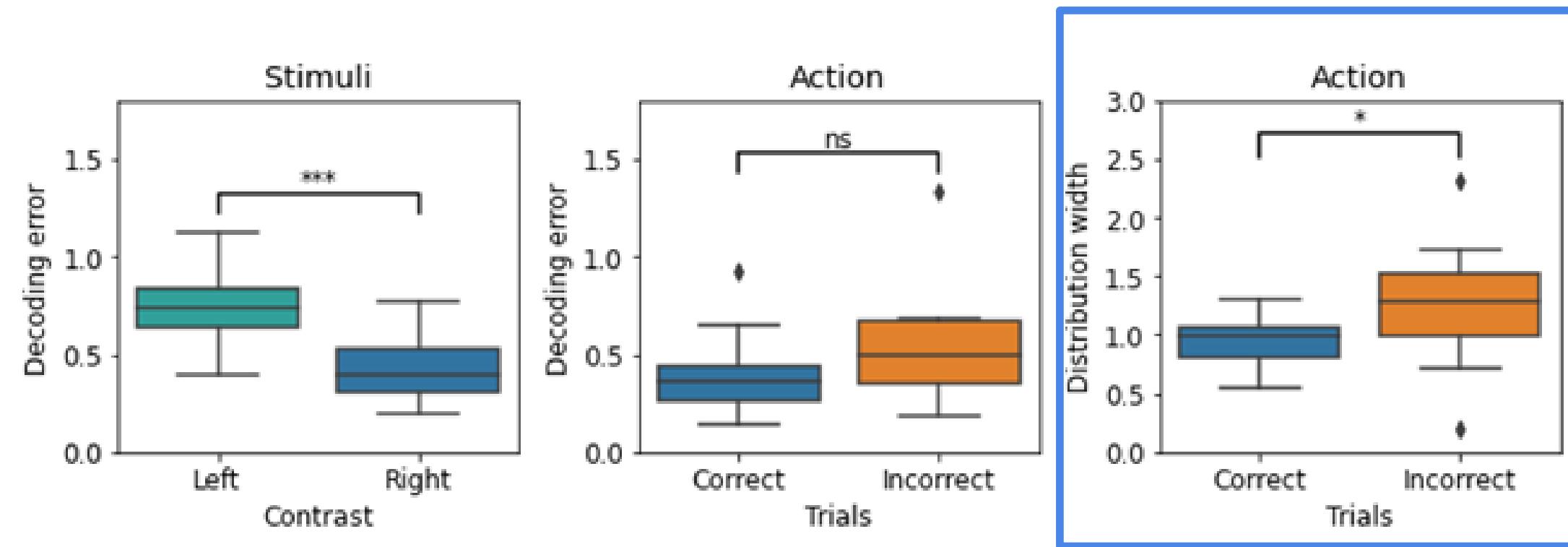
11 sessions V1

Bayesian decoder in V1:

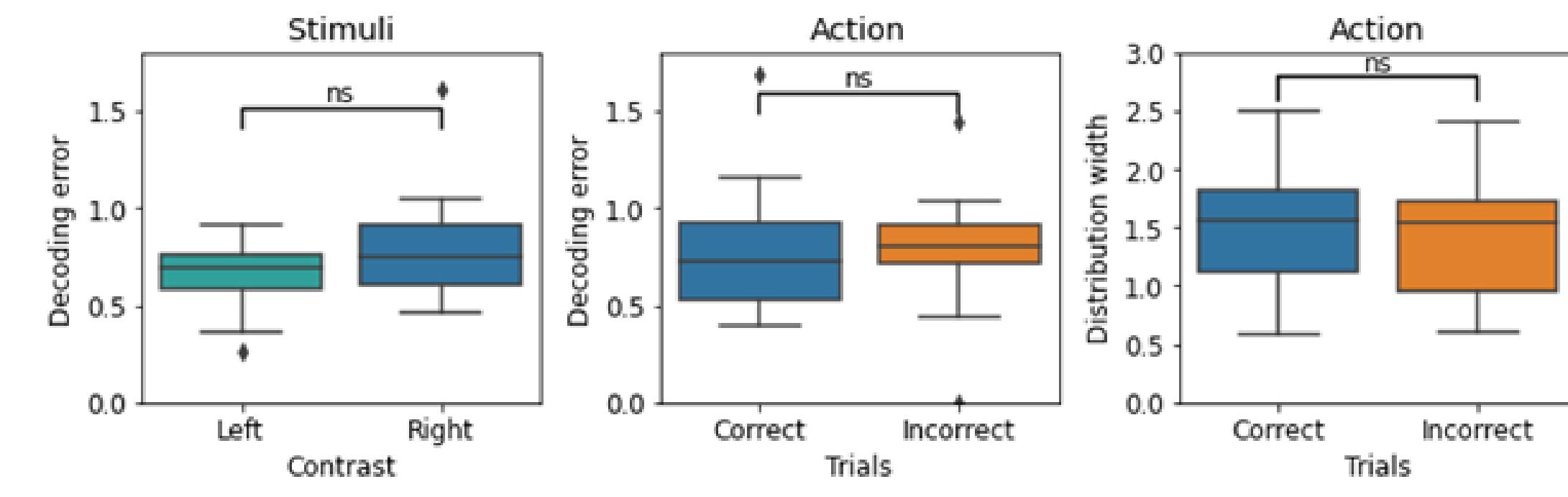
- Successfully decodes right (contralateral) contrast modulations
- Cannot decode left contrast modulations which were less well represented within tuning fields
- Decoding error is not predictive of animal performance
- Variability in neural responses can be predictive of animal performance

What about other recorded regions?

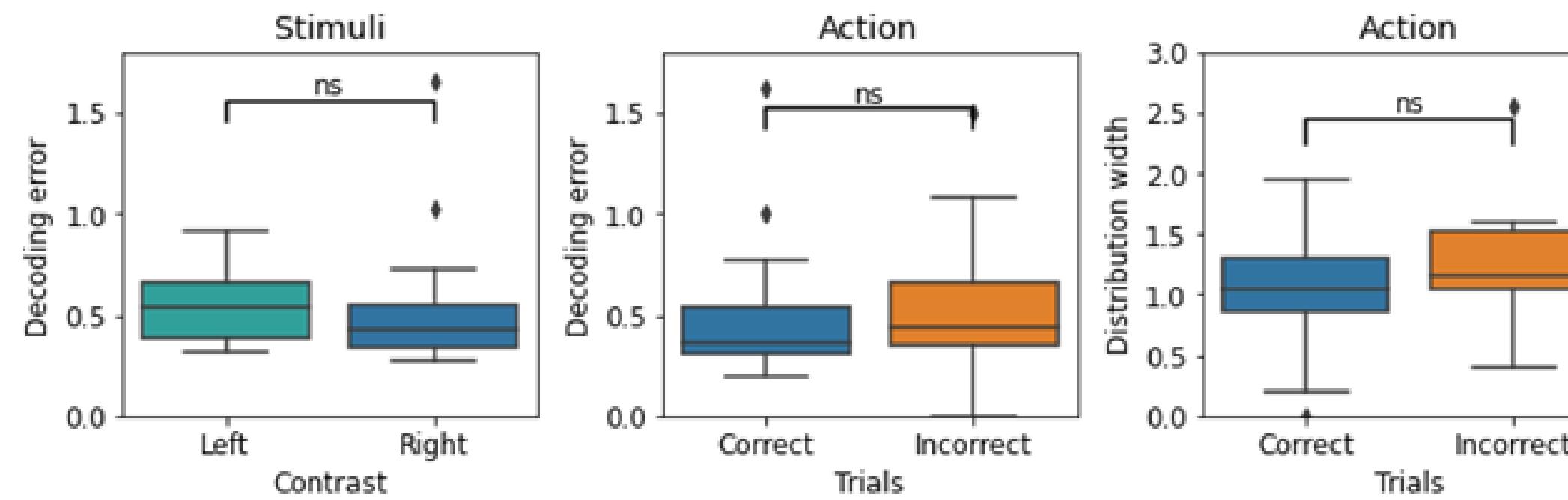
VISp



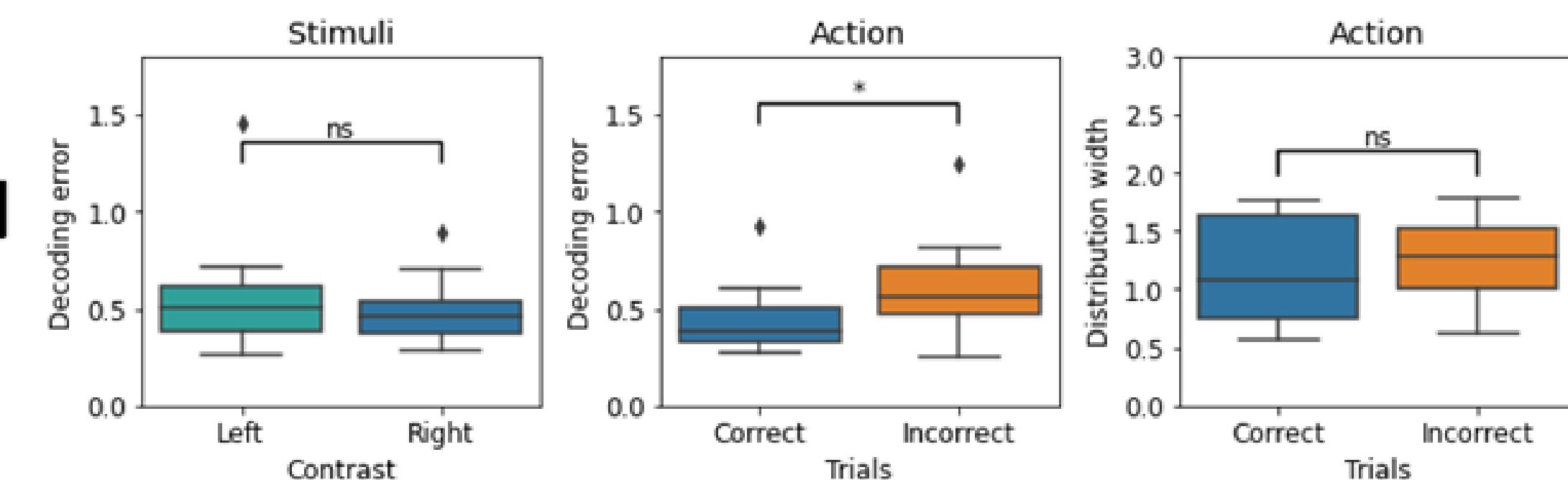
CA1



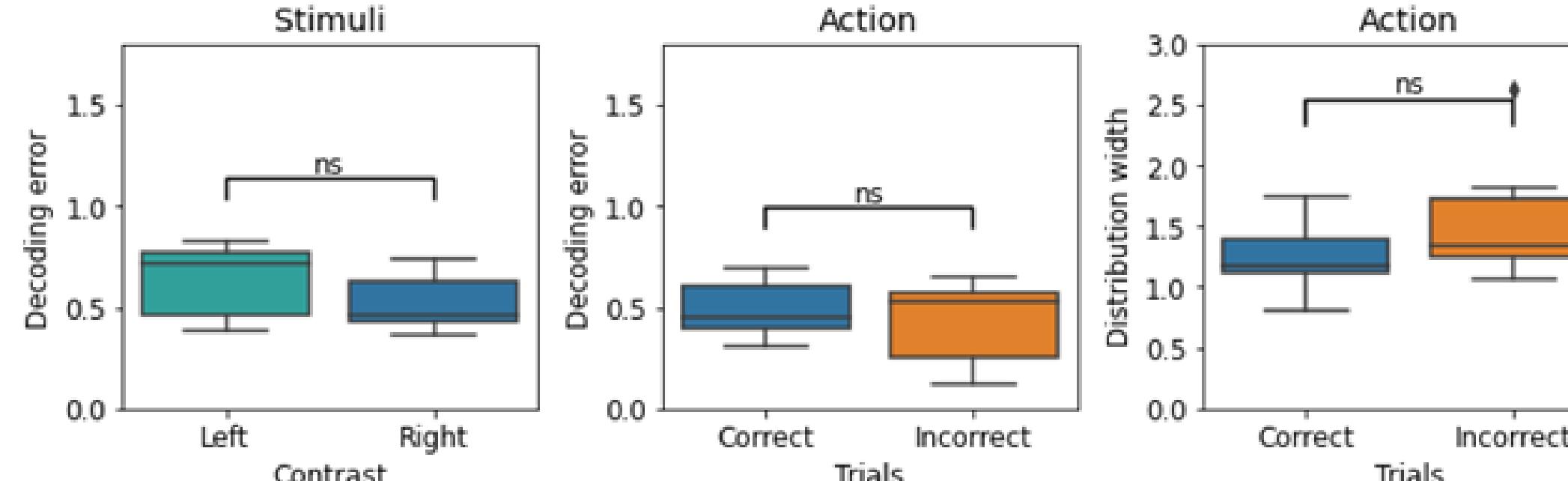
MOs



MRN



LGd

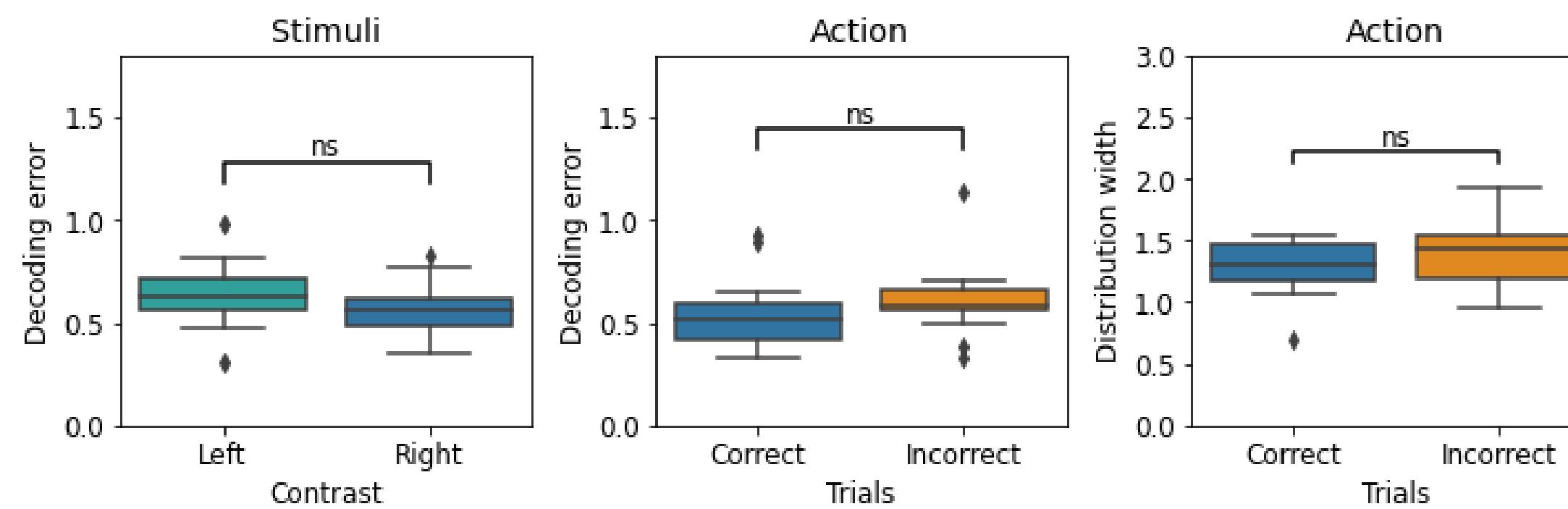


Probability distribution width in other regions than V1 was not predictive of animal performance

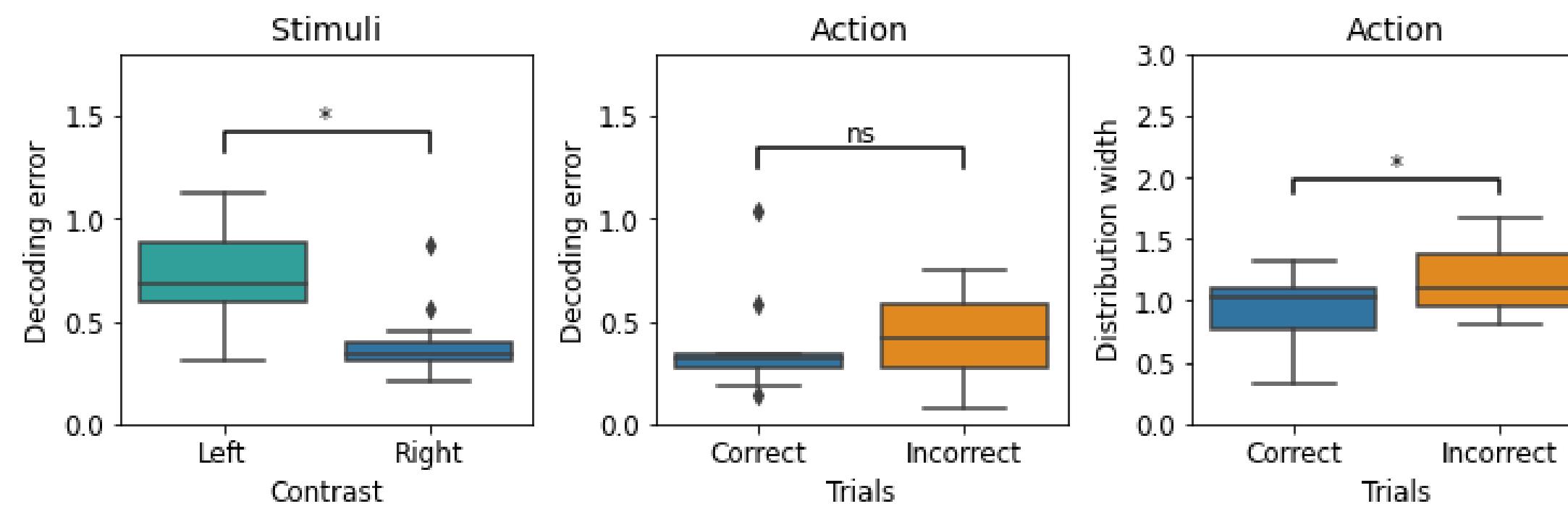
Control analyses

Unit selection

Non contrast modulated cells only (V1)

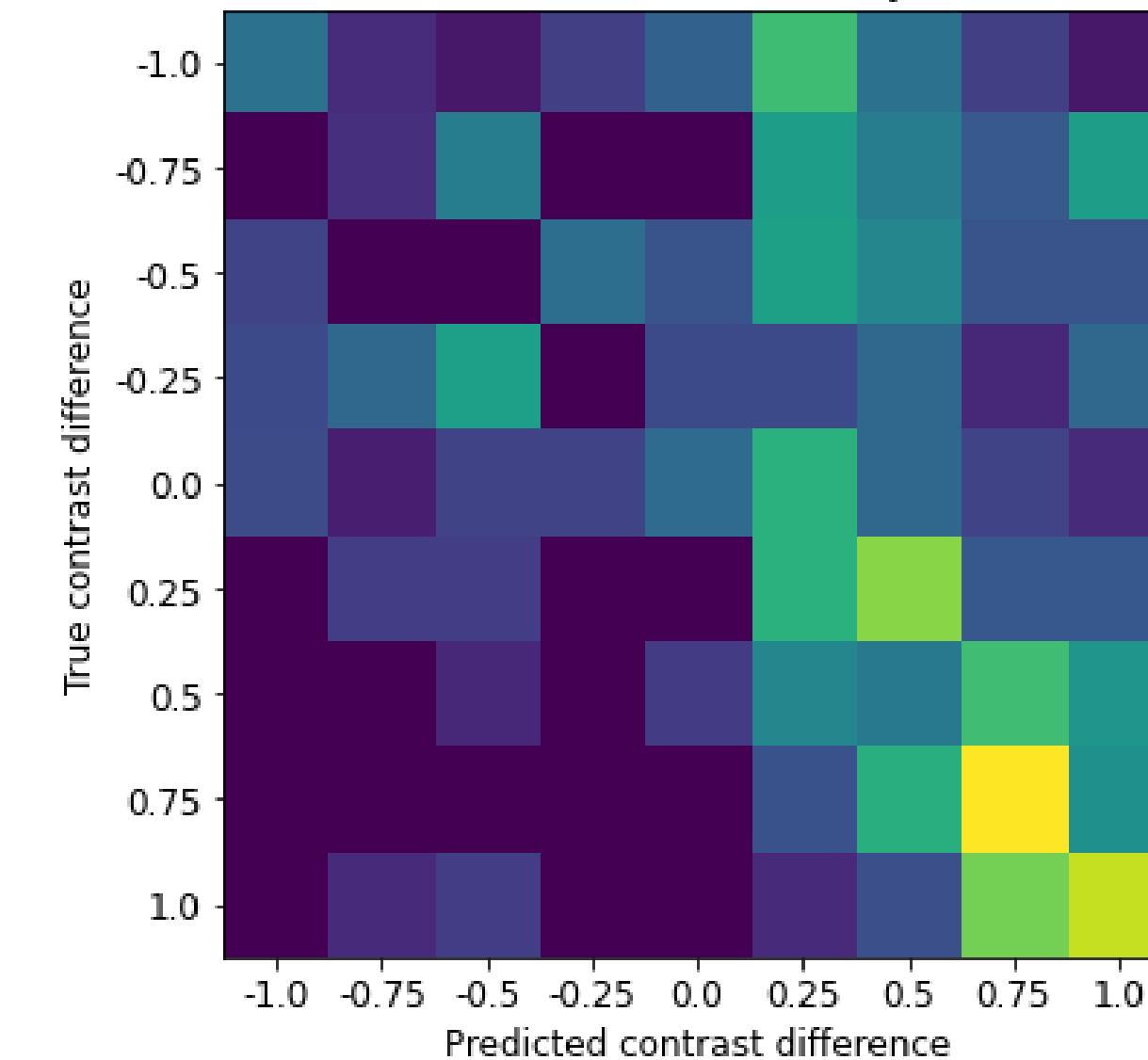


All recorded cells in V1

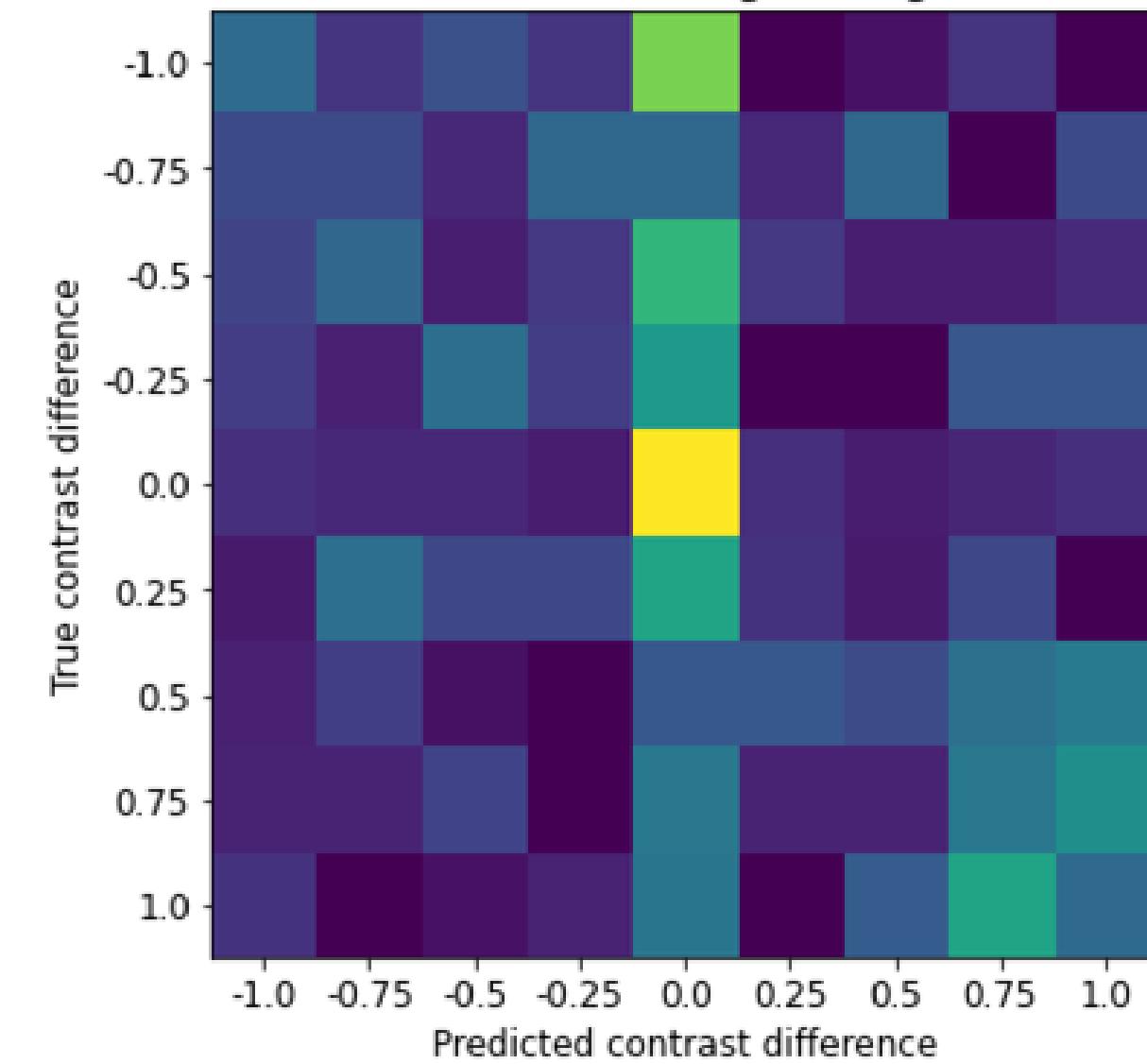


Comparison to logistic regression

Confusion matrix - Bayes



Confusion matrix - Logistic regression



Bayes

All trials: 0.528
 Left: 0.875
Right: 0.324

Logistic regression

All trials: 0.346
 Left error: 0.648
 Right error: 0.598

Limitations & Pitfalls

- Sub-selecting cells can cause bias
- Having recordings only from left visual cortex → we could only decode contrasts shown on the right
- Generating tuning curves based on contrast difference
- Limited sampling of cells from each area
- Assumption of independence of cells
- Assumption of neurons emitting spikes following a Poisson process

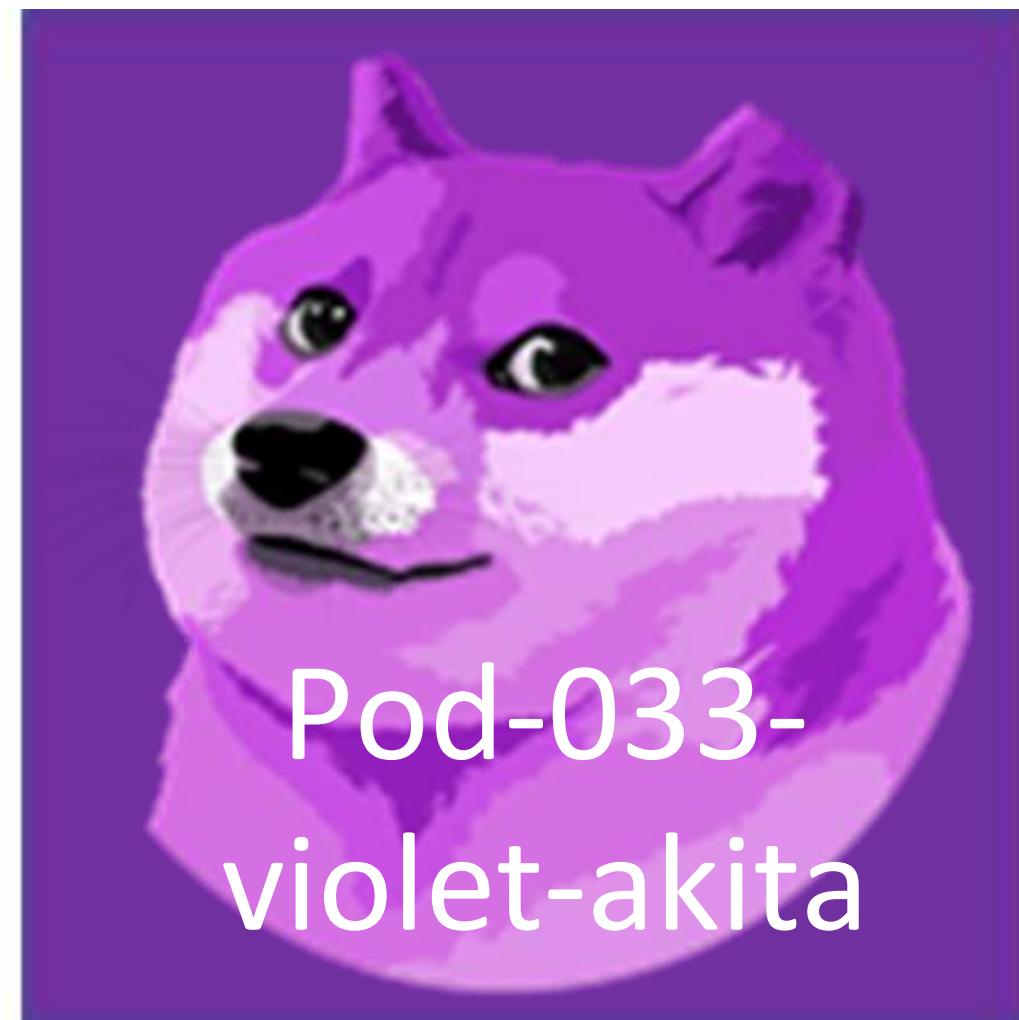
Acknowledgements



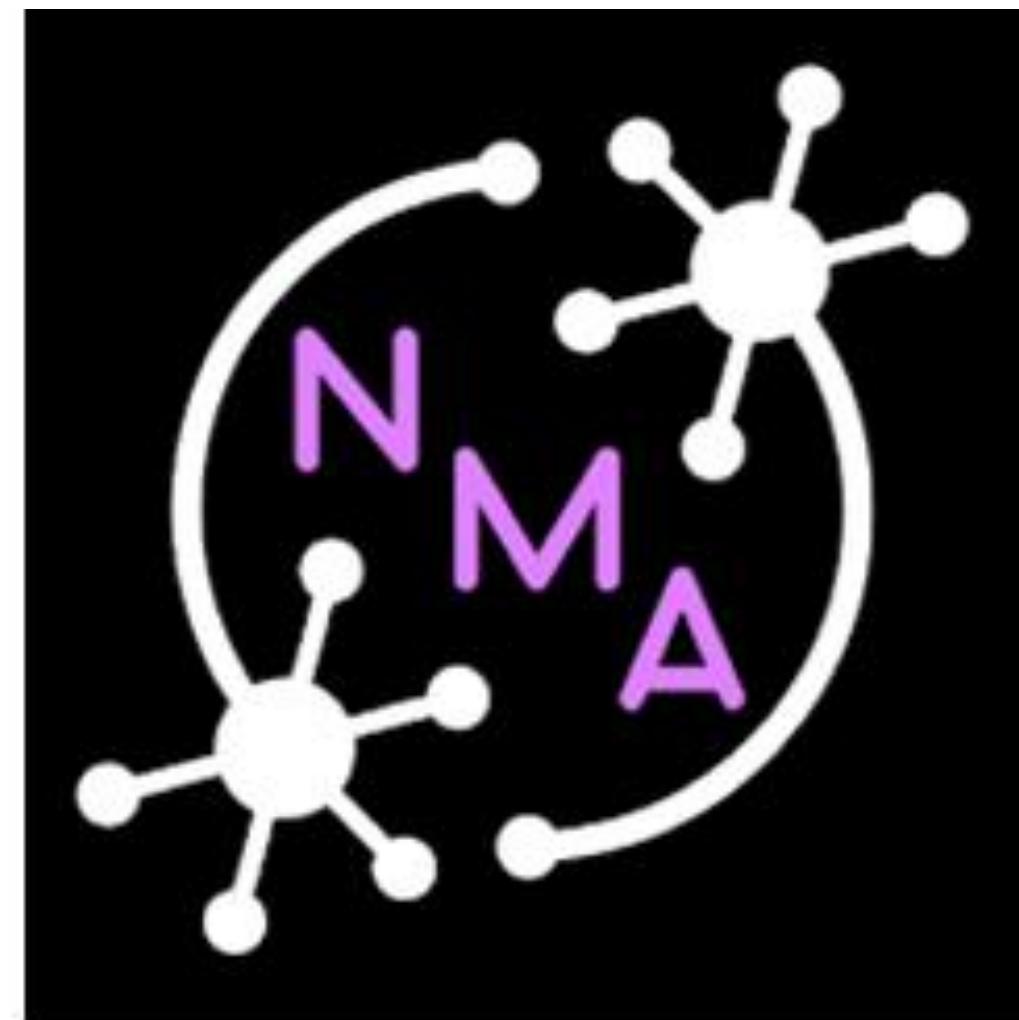
TA:
Emma Roscow



Mentor:
Adrien Peyrache



**Our
Pod**



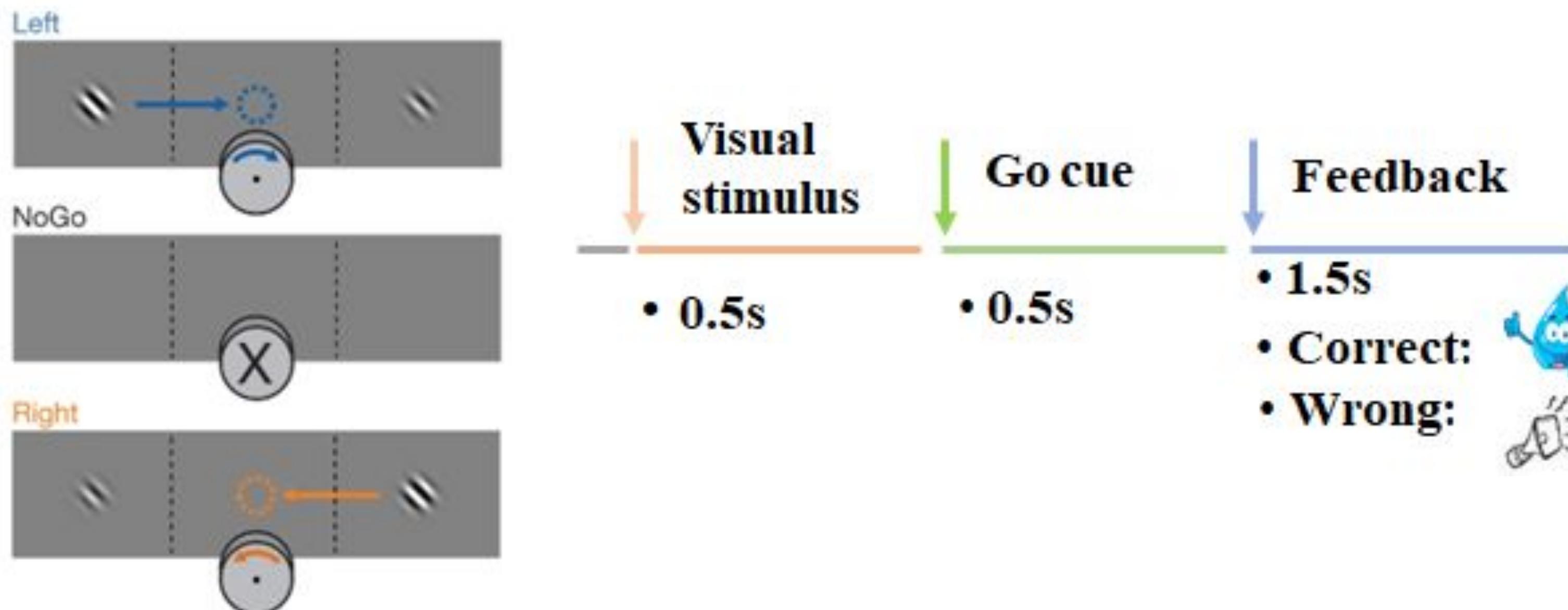
**NMA
Organizers**

Explore-and-exploit

Project member: Yasuo Kabe, Xiaoli Wu, Chunyue Li

Question: How does the neural activity in the whole-brain scale represent trial history factors extracted from behavior?

Dataset: Steinmetz decisions

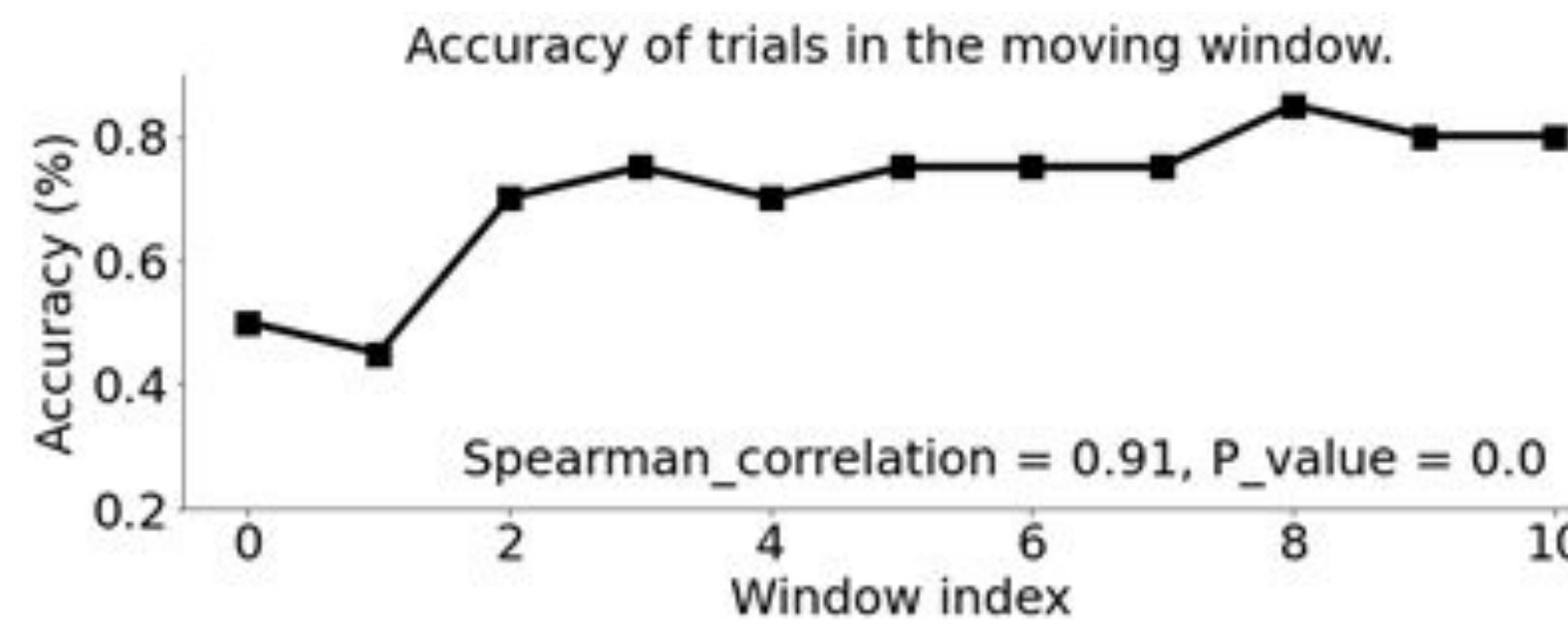
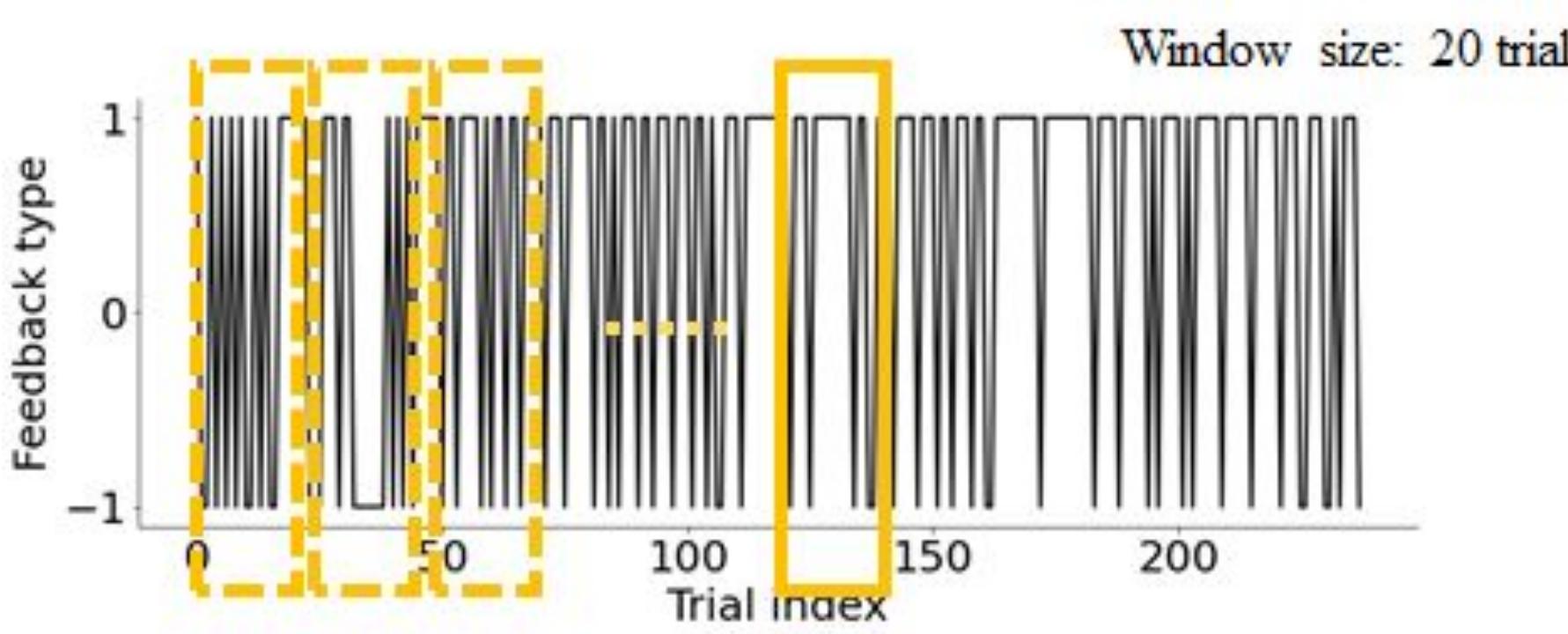


Acknowledgments

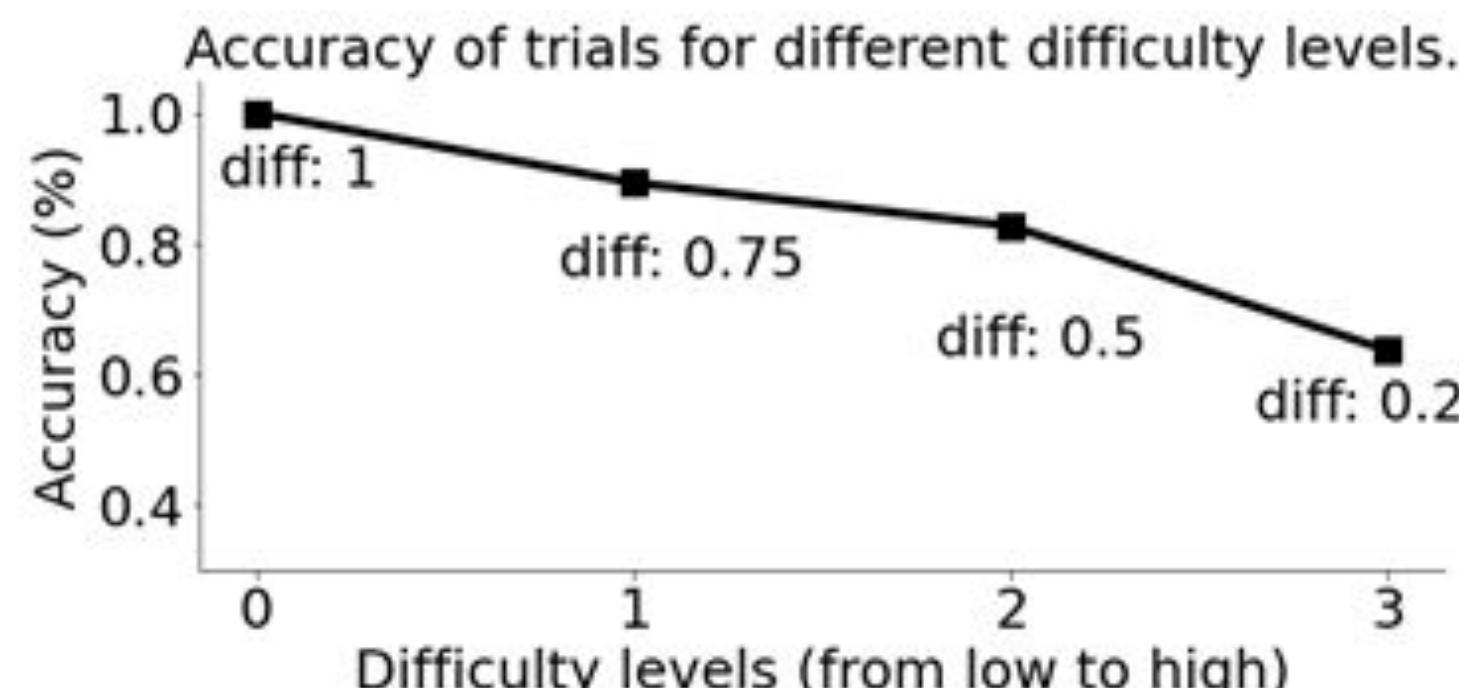
- Sofya Kulikova
- Joshua Dudman
- Zhang Lei
- Mahsa Alizadeh Shalchy
- Nattapat Tanjariyaporn
- All NMA staff members!

Mouse: Forssmann, session 4

- Accuracy increases over time



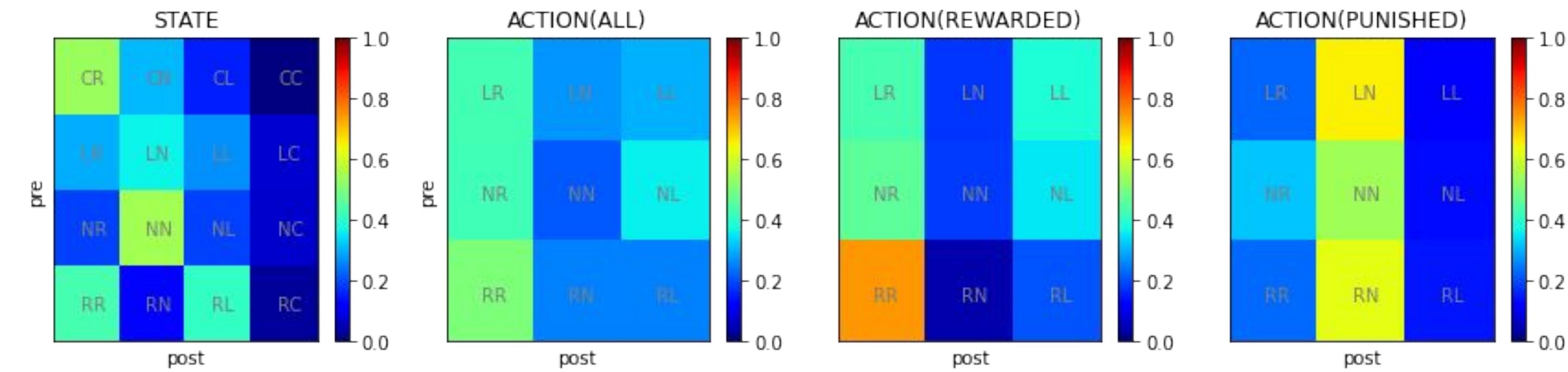
- Accuracy decreases with increasing difficulty



Diff: absolute contrast difference between two visual stimuli

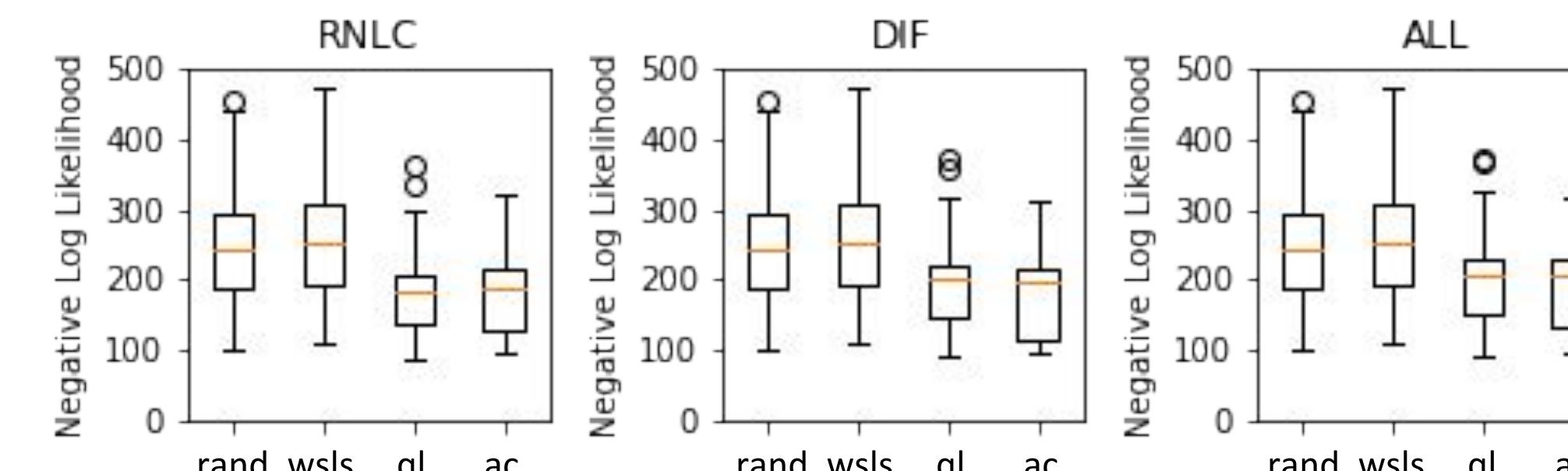
- Transition Probability of States and Actions

Mice exhibited different action depending on previous action's outcome

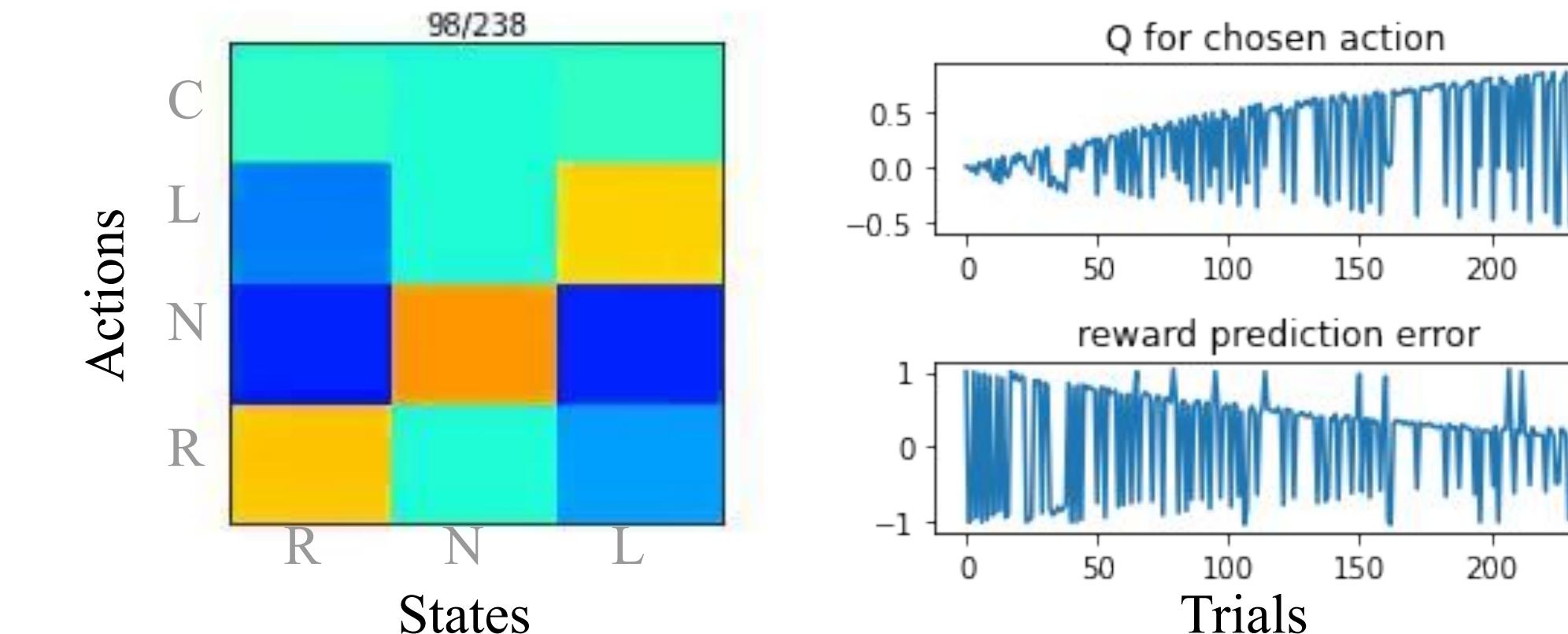


- Comparison of State Representations and Models

Q-learning model with 4 state representation yielded high likelihood



- Selected Q-value and Reward Prediction Error



R, right; N, no go;
L: left; C: chance

State Representations

RNLC: right, no go, left, chance

DIF: right and left contrast differences

ALL: all right and left contrast pairs

Models

rand: fixed p(a)

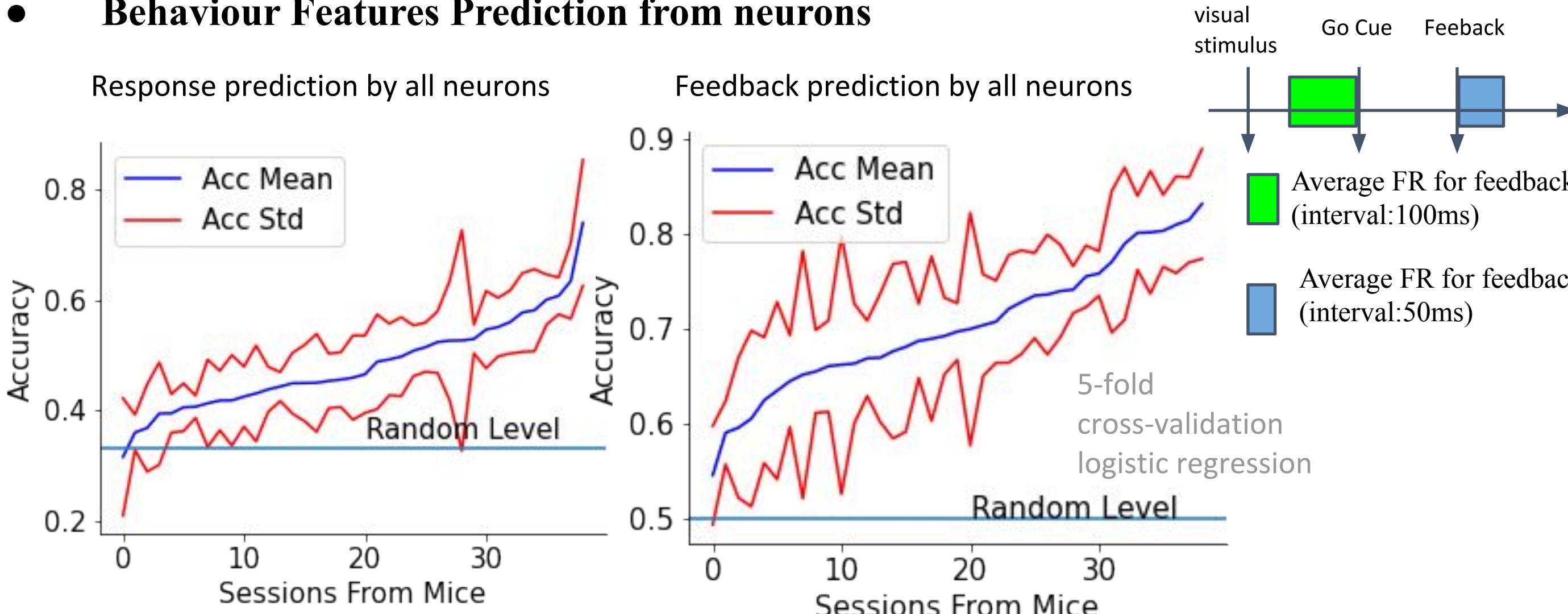
wsls: Win-Stay-Lose-Shift

ql: Q-learning

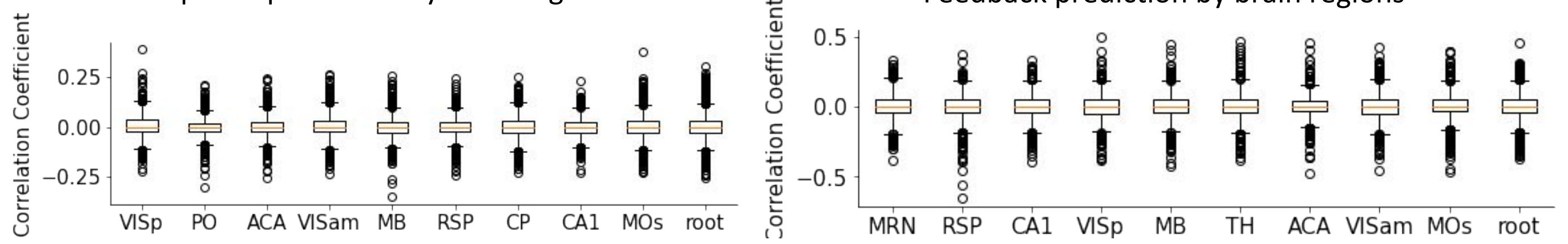
ac: Actor-Critic

• Behaviour Features Prediction from neurons

Response prediction by all neurons

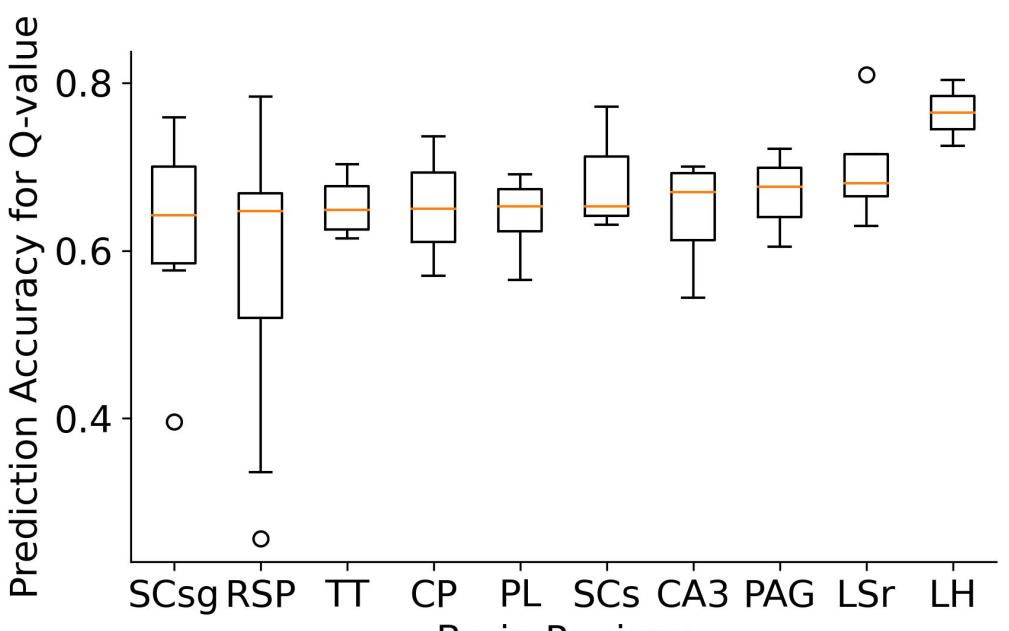


Response prediction by brain regions

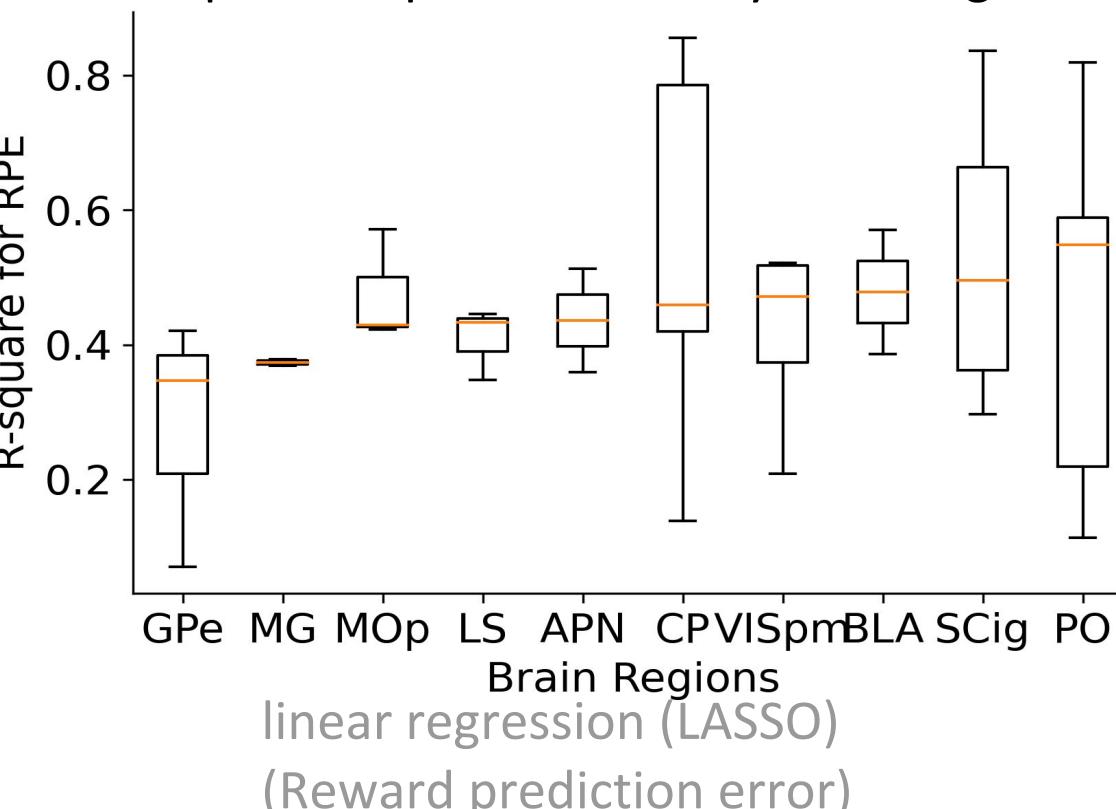


• Latent variables prediction by neurons from different brain regions

Top 10 Q-value prediction by brain regions



Top 10 R-square for RPE by brain regions



• Conclusion & Discussion

1. Task Performance

- ★ The significant positive correlation means that a learning process exists in this session of the mouse Forssmann.
- ★ This learning process is not common in well-trained behaviors. Only one session found this process in Steinmetz's dataset.
- ★ Mouse performs better in low difficulty tasks.

2. Trial History in Behavior

- ★ Mice's action in the current trial depended on the outcome of the previous trial, indicating effect of trial history.
- ★ Q-learning model provided the best fit to behavioral data (amongst the models tested). This suggests action selection was based on states while incorporating trial history.
- ★ State representation using required action provided the best fit to behavioral data. Preference of state representations with smaller number of states is facilitated by the ease in state space exploration.

3. Neural Activity and Trial History

- ★ Using firing rates from all recorded neurons can predict the behavior features (feedback type, response type) well.
- ★ Some brain regions have neurons highly correlated with the behavior features (feedback type, response type).
- ★ Neurons in some brain regions can be used to predict the latent variables (Q-value), like Lateral Habenula (may be related to reward-punishment).
- ★ Neurons did not strongly correlate with reward prediction error.

The Link Between Correlated Variability And Performance

Neuromatch Academy
July 30th 2020

The Flame Pistols

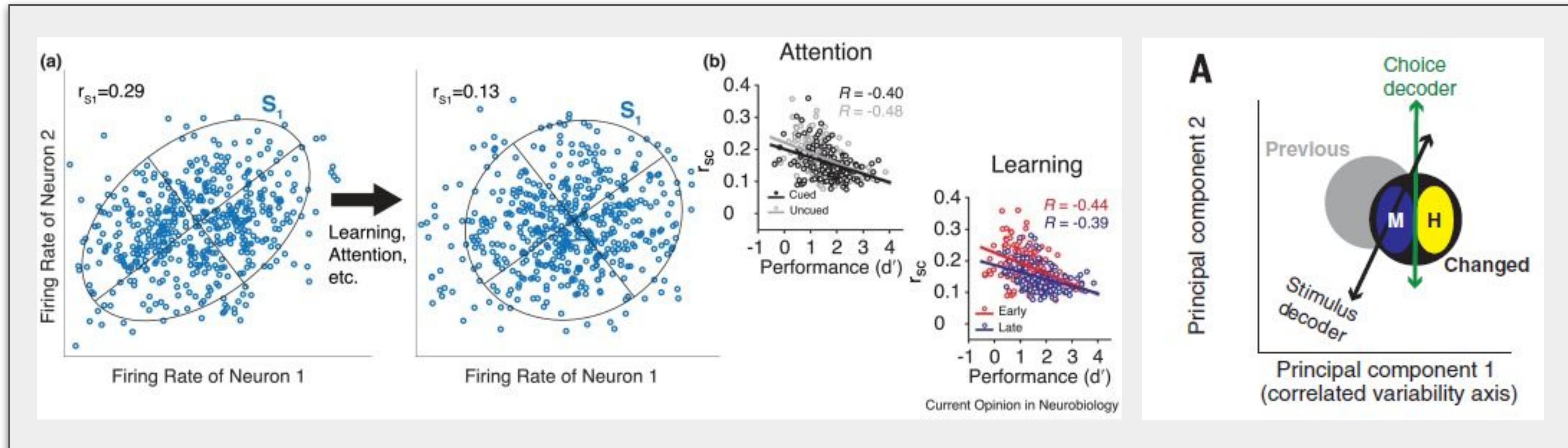
Sweta Agrawal, Leor Katz, Laura
Gomez, Nour Rimani, Kyrstyn Ong



How does correlated variability relate to performance?

Previous studies show:

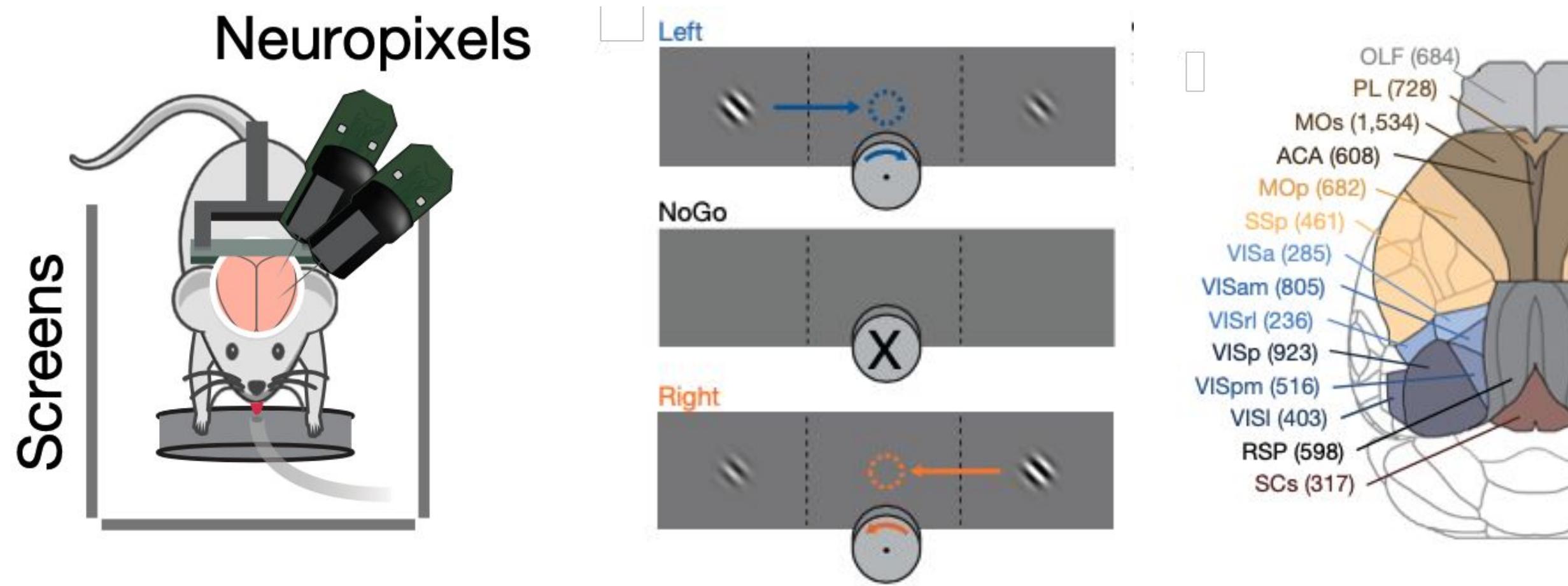
- Reduction in r_{sc} with increased performance during attention, learning, and task engagement
- Correlation between r_{sc} and 1st principal component
- Correlation between r_{sc} and accuracy of choice decoder



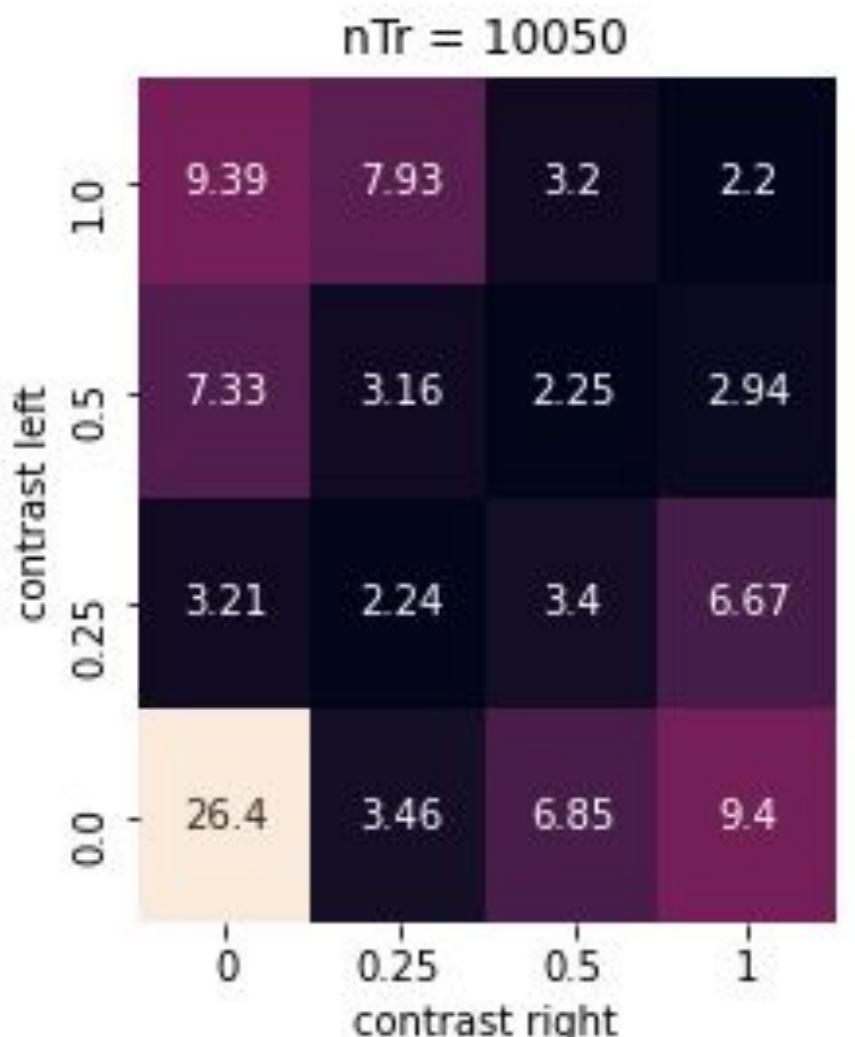
Saxena and Cunningham, 2019
Ni et al, 2018

Decoding performance via the Steinmetz Data Set

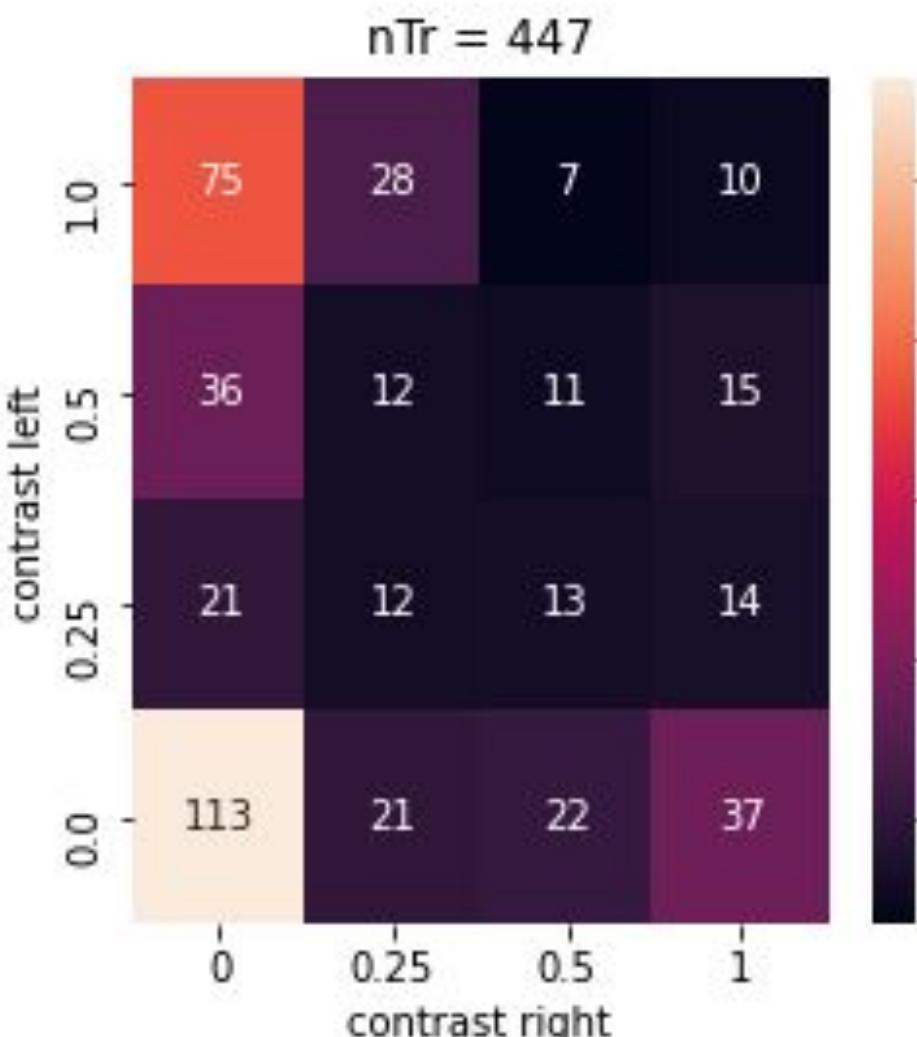
(Steinmetz et al, 2019)



Total proportion of trials per stimulus condition

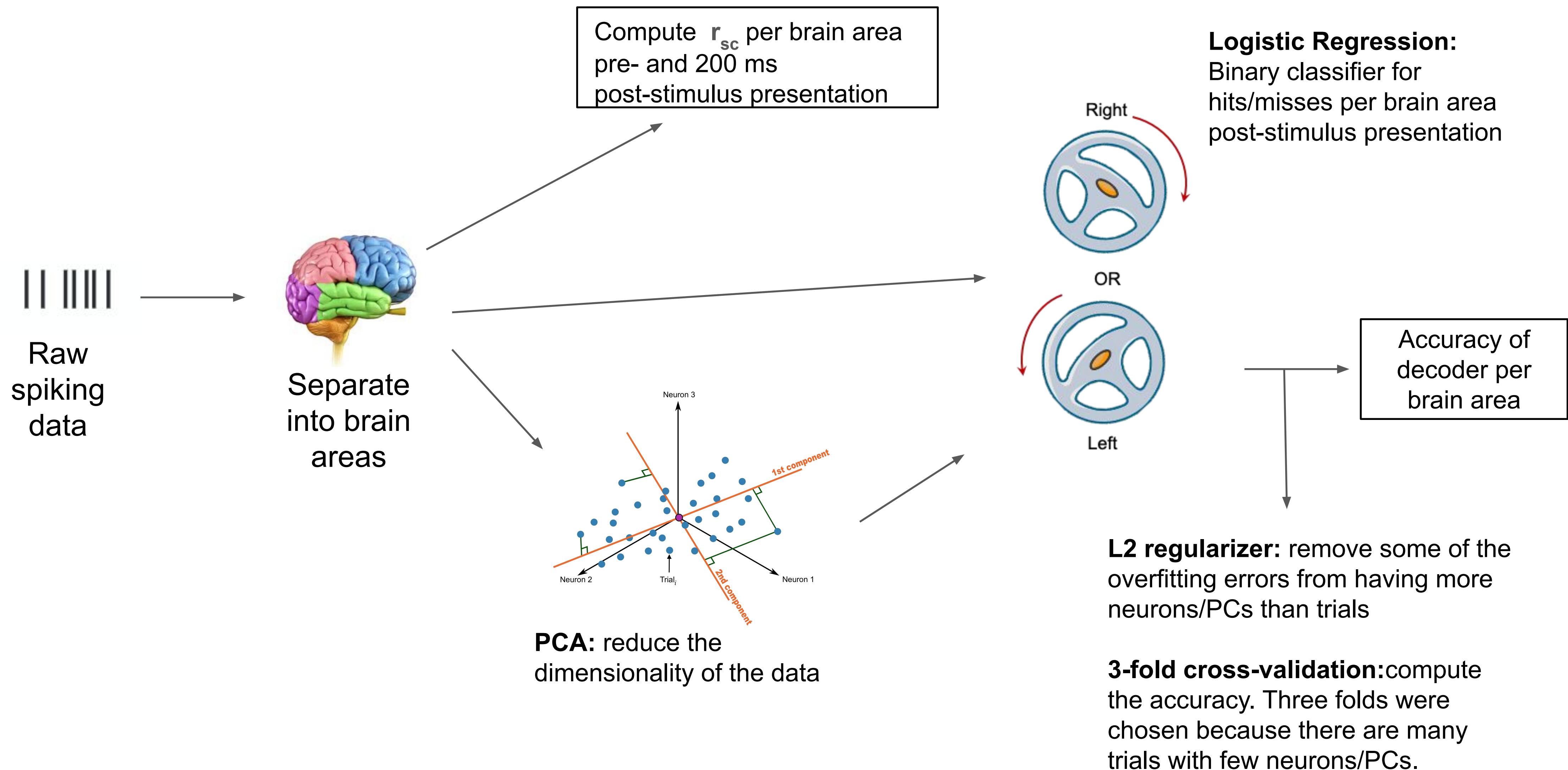


Trial count per stimulus condition in example session



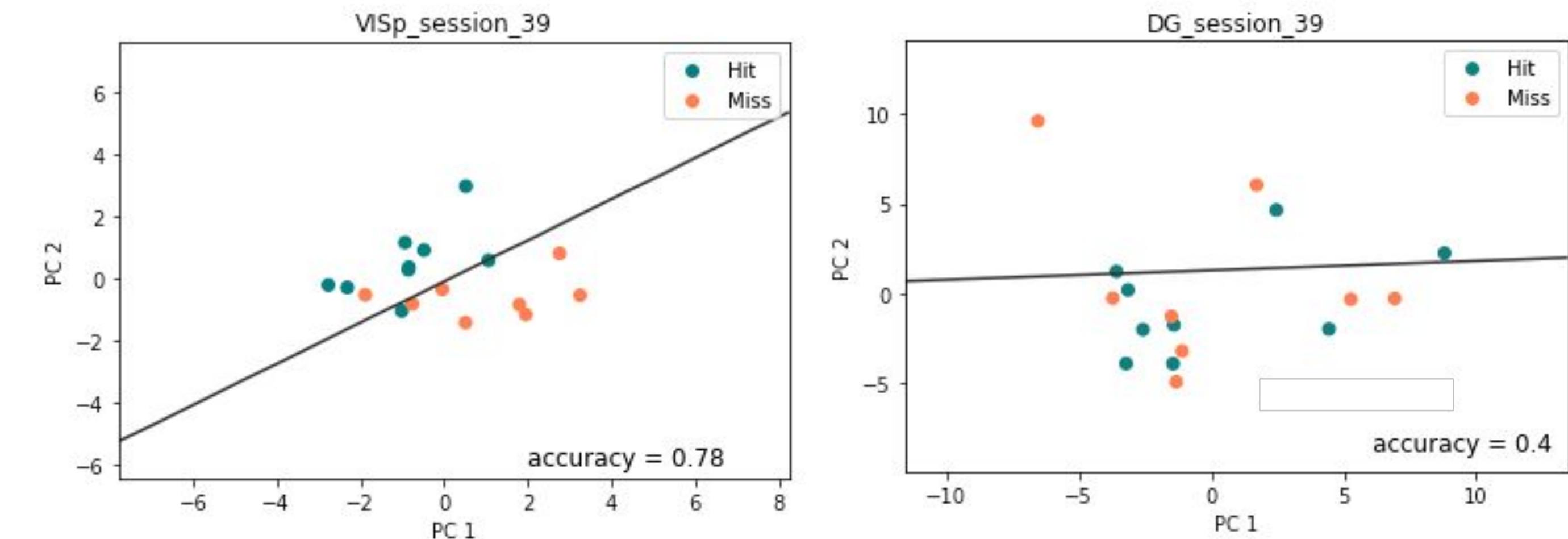
Because correlated variability (r_{SC}), is computed on identical stimulus condition trials, we had to focus on per session and per trial analyses, which dramatically limited our working data set.
We focused on the [0,1] & [1,0] contrast conditions.

Goal: Determine the relationship between the r_{sc} and accuracy of the binary classifier for each brain area.

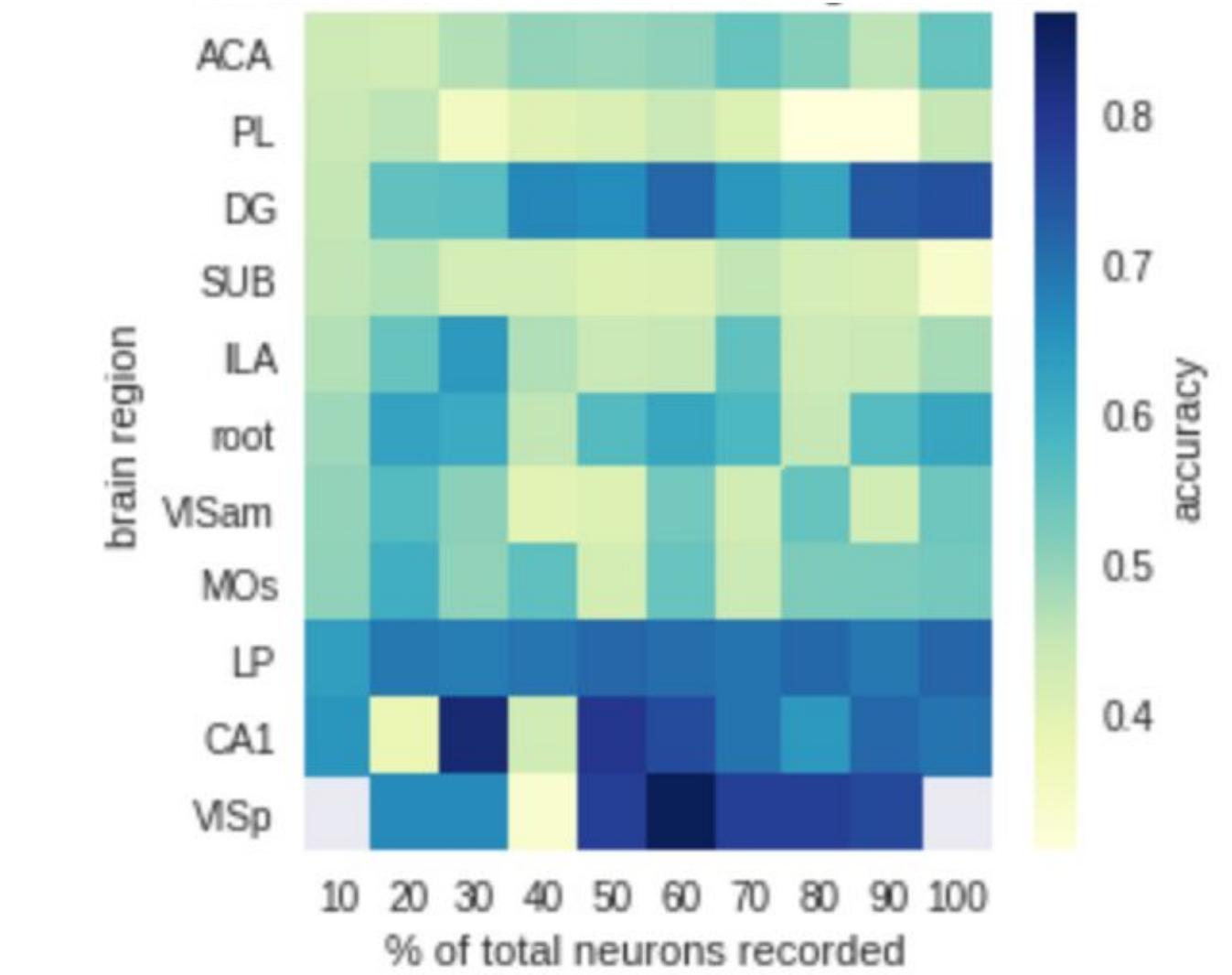
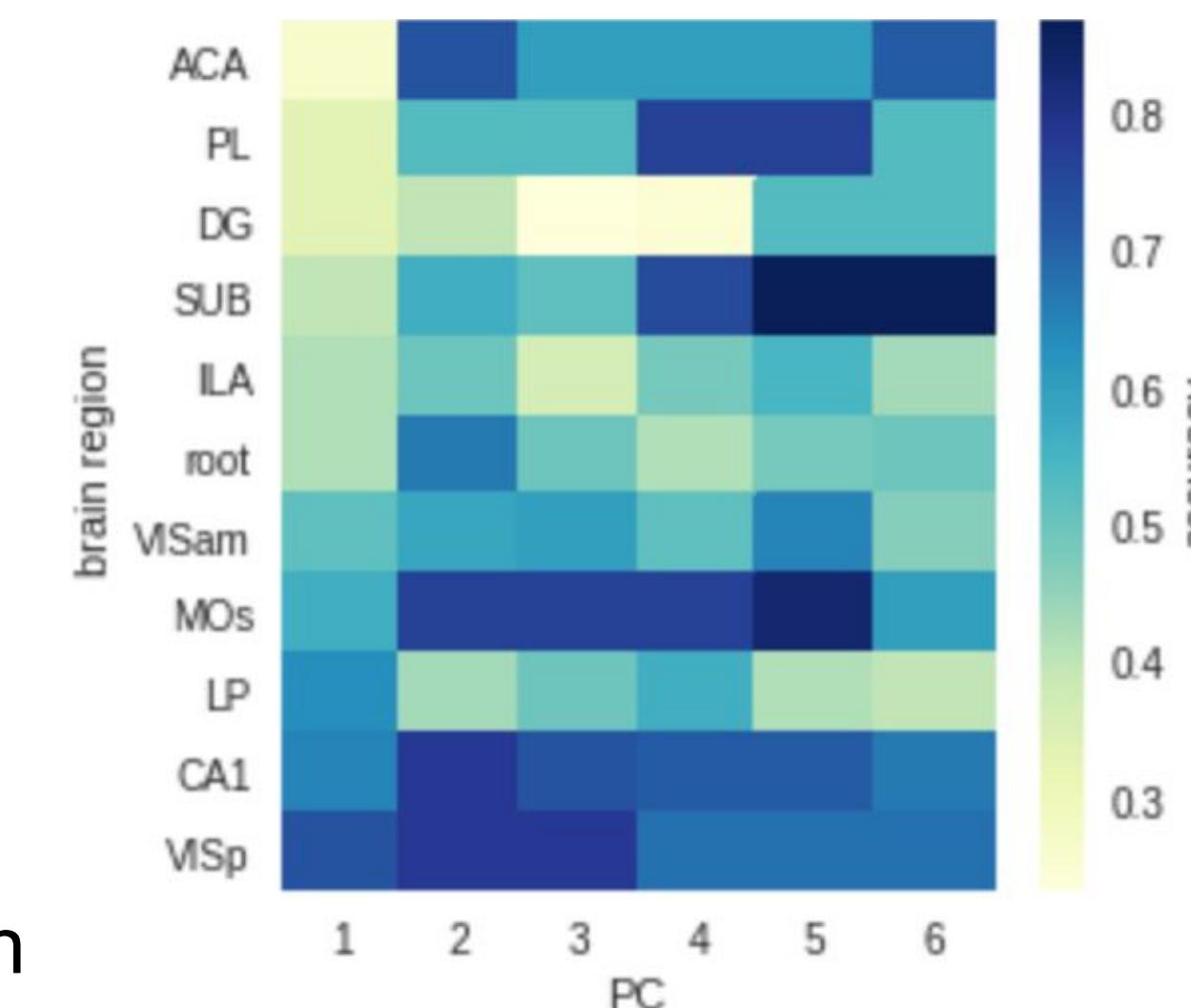


Binary Classification of Hits vs Misses:

- Logistic Regression → classify hits vs. misses across brain areas for particular stimuli presentations
- Obtained different results when raw spikes were used as inputs to the model instead of PCA components
- Determined that increasing the % of total neurons/PCs recorded did not increase the test accuracy in each brain area. This is likely due to the sparsity of recorded neurons in certain brain regions as well as the lack of many misses in a session (see appendix).

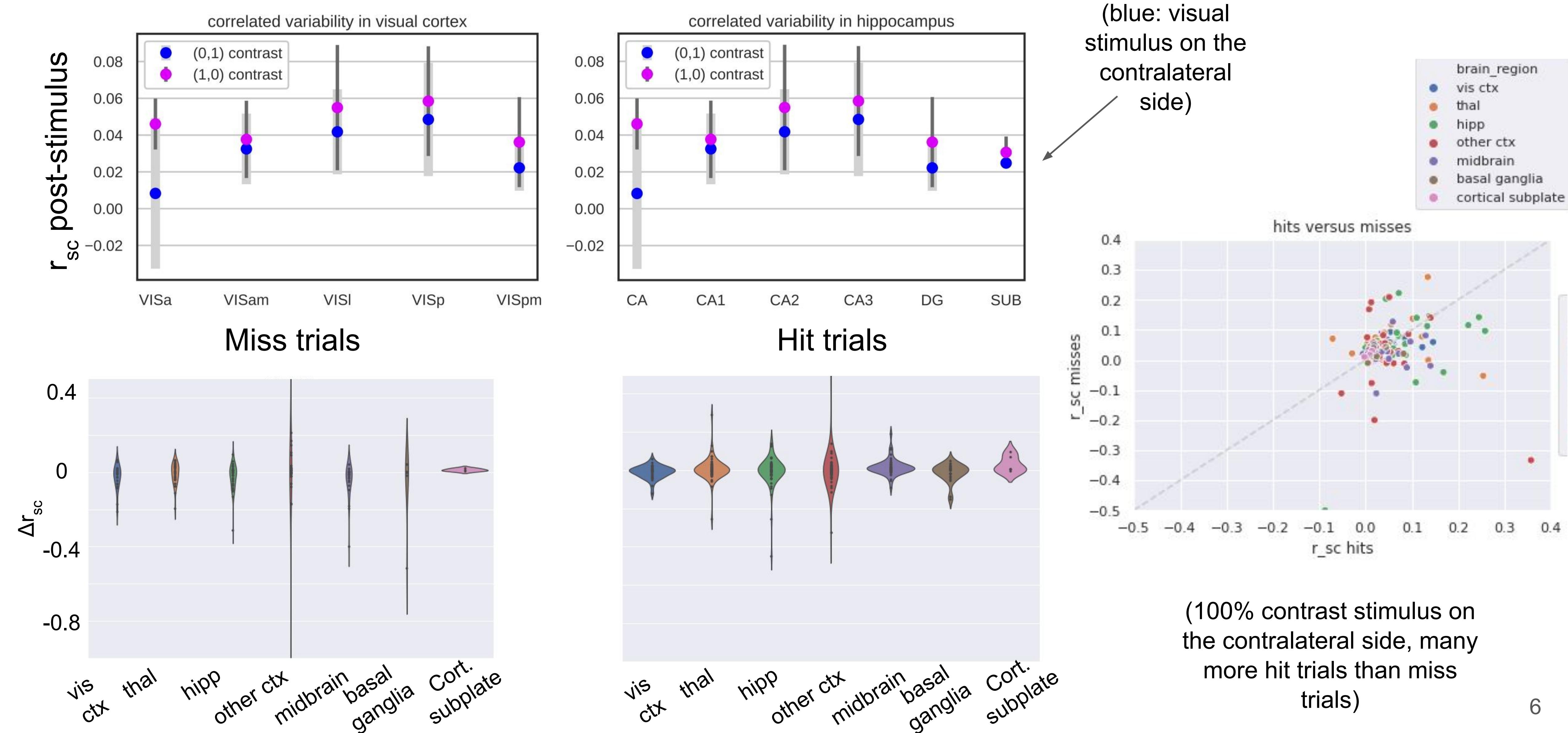


Effect of increasing PCs vs Neurons on Test Accuracy



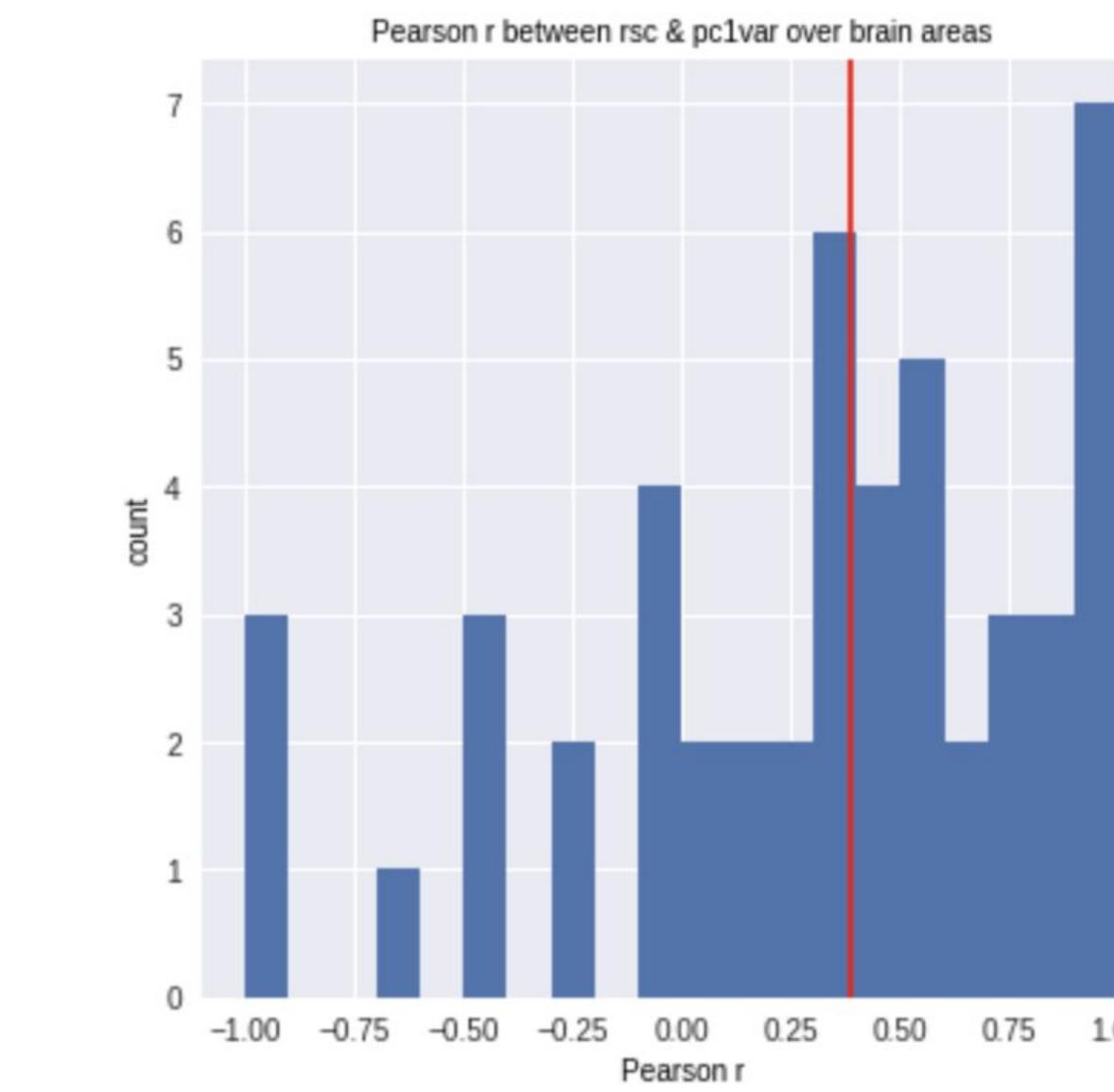
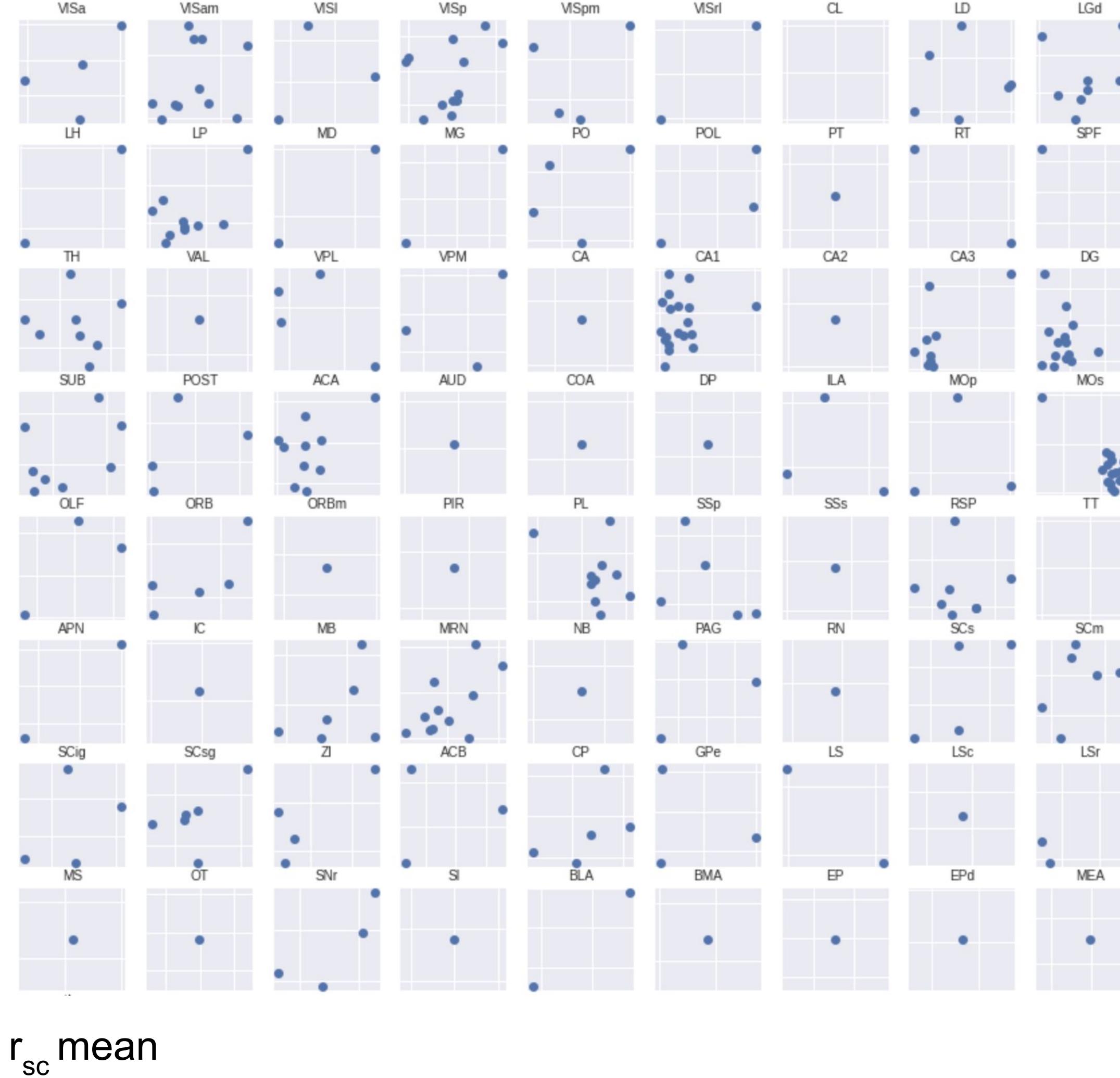
These plots were created with data from session 39 with the stimulus contrast of right 1 and left 0.

r_{sc} over stimulus conditions and performance



r_{sc} is captured by the 1st PC in many brain regions

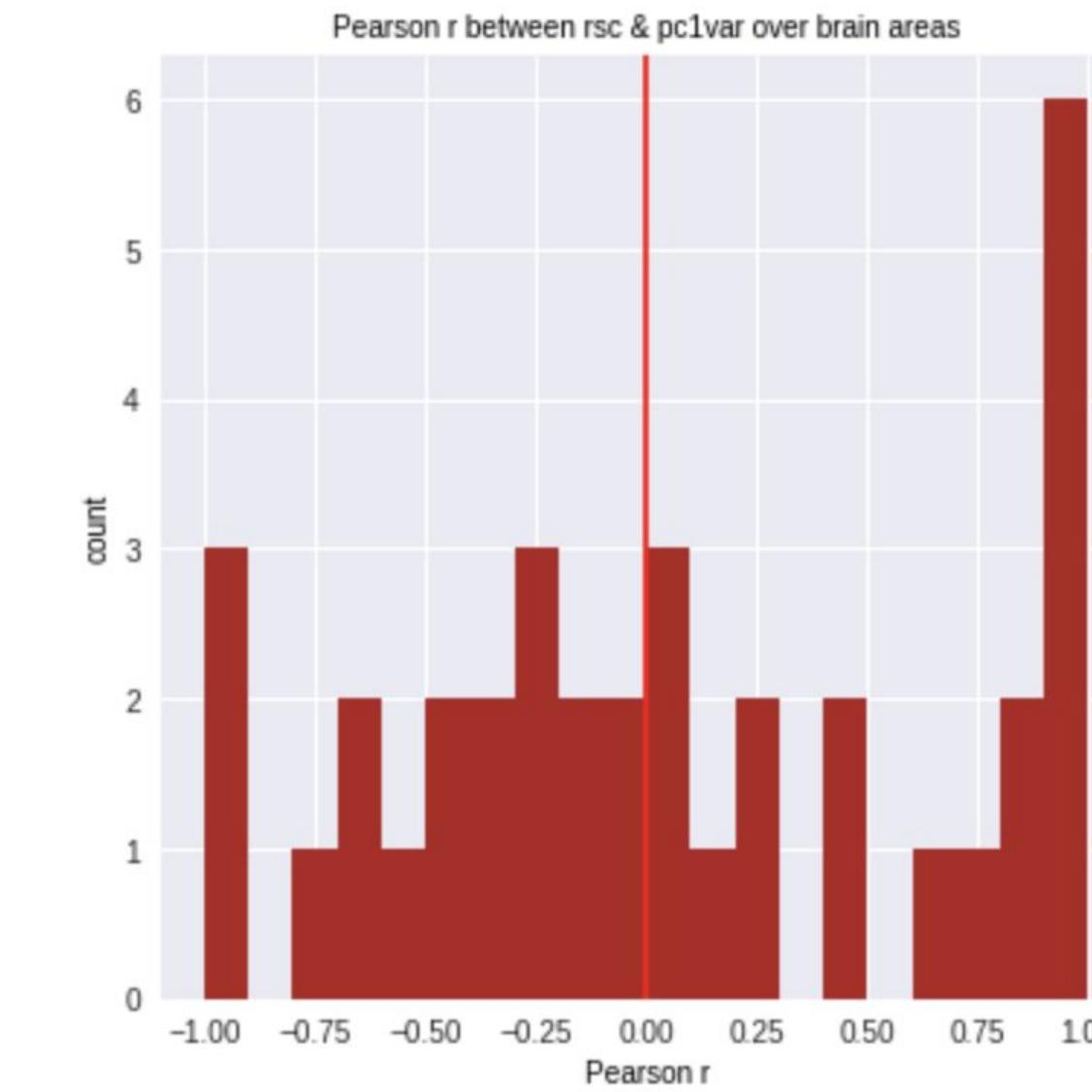
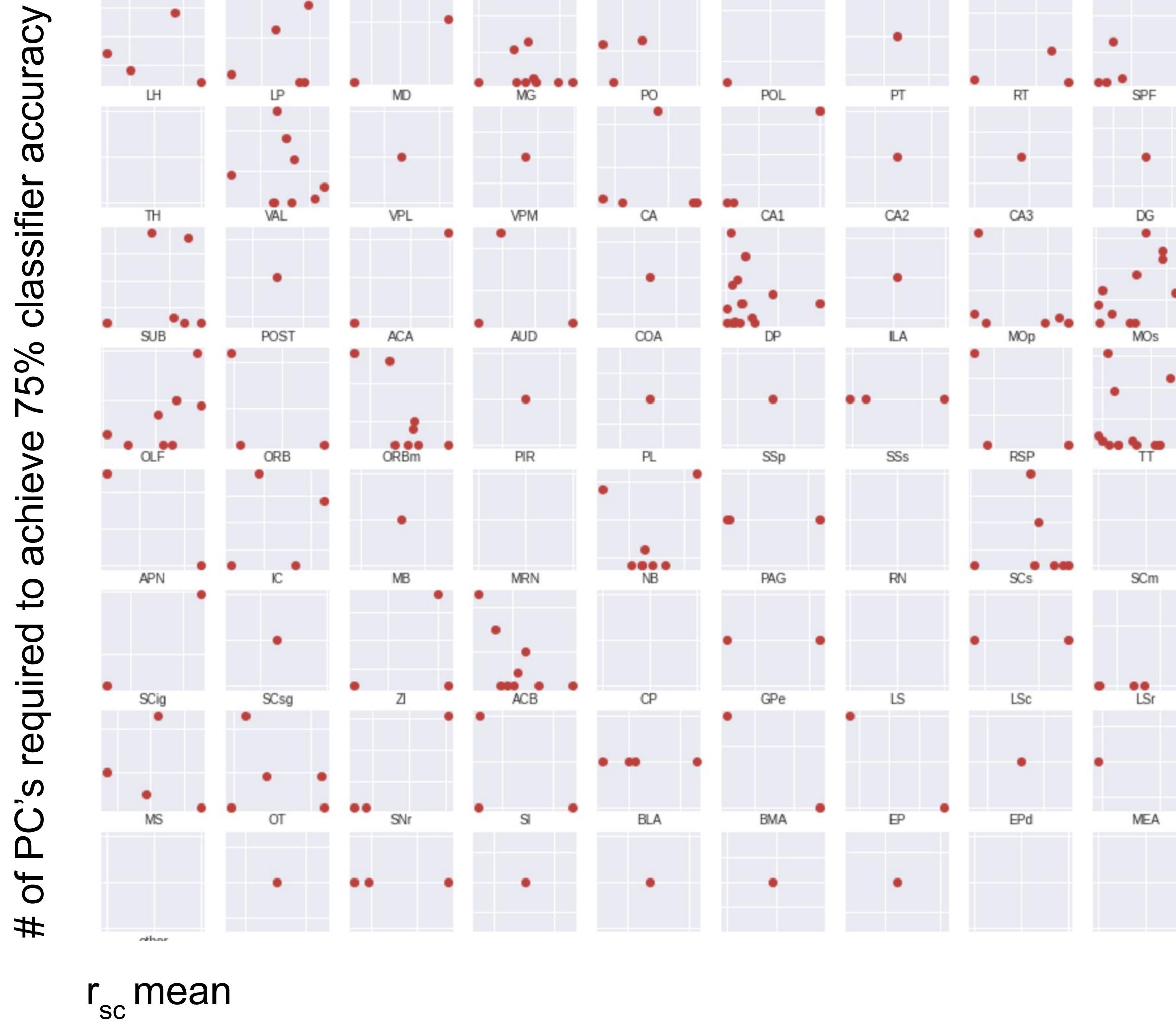
Variance explained by 1st PC



Across brain areas, variance explained by the 1st PC is largely correlated with r_{sc}

This indicates that a large proportion of neural variability in these ensembles is due to r_{sc}

No systematic relationship between r_{sc} and classifier



Across brain areas, # of PC's required to achieve 75% classifier accuracy varies.

This indicates that the r_{sc} in some brain areas is more directly related to behavioral performance than in others.

Challenges:

- Restricting our analysis to trials with the same stimulus being presented drastically reduced statistical power
- For stimulus conditions with sufficient trials, we had a limited number of incorrect “miss” trials, which limited our decoder’s performance
 - Separating “incorrect” from “miss”
- Not all brain areas were samples equally, leading to inconsistencies in power.

Looking ahead:

- Looking at a period of time conditioned on the mouse’s movement rather than stimulus presentation
- Alternative methods of dimensionality reduction, such as dPCA
- Stimulus decoder instead of a performance decoder

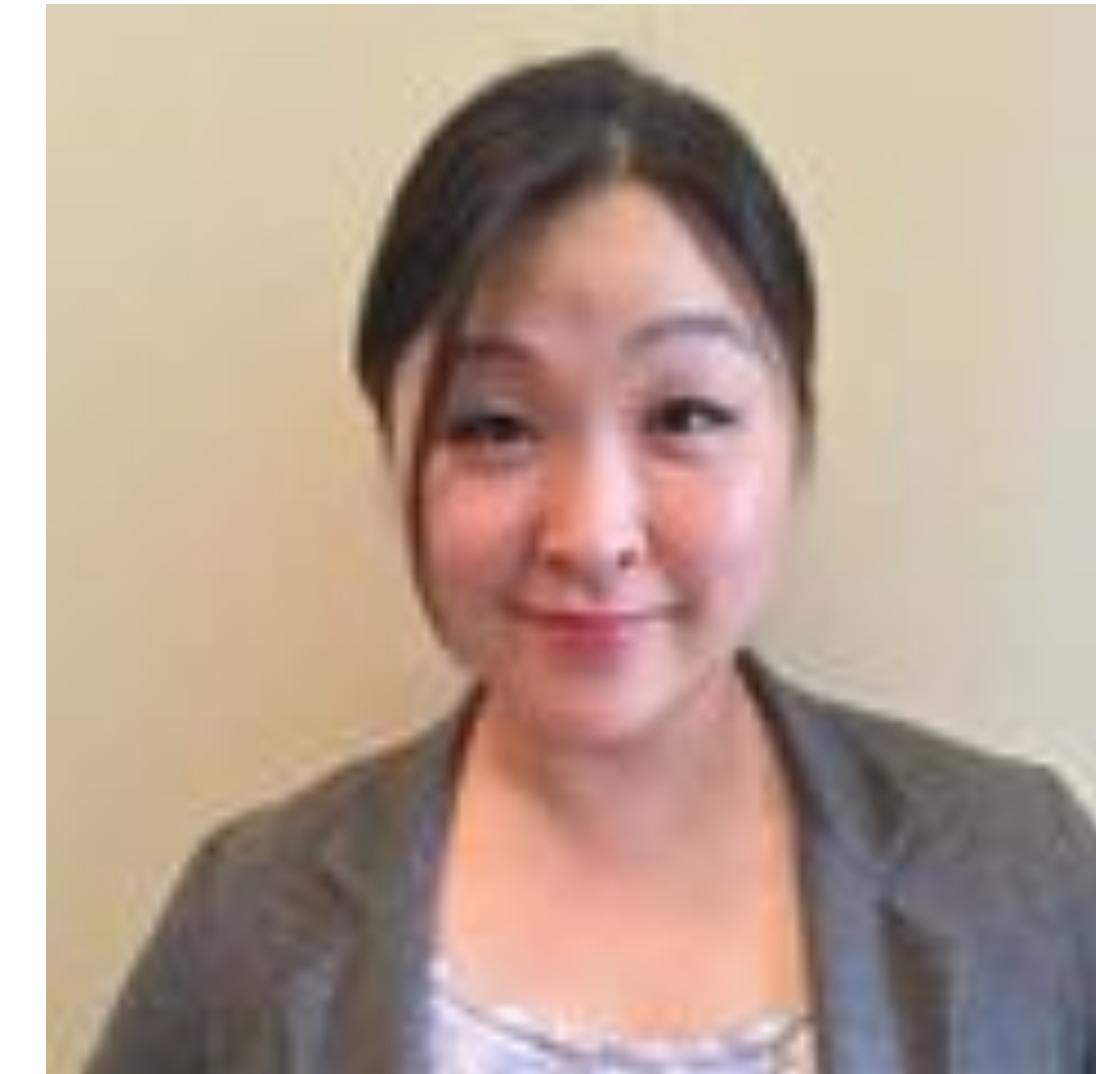
Thank you!!



Shreya Saxena



Suresh Krishna



Amy Ni

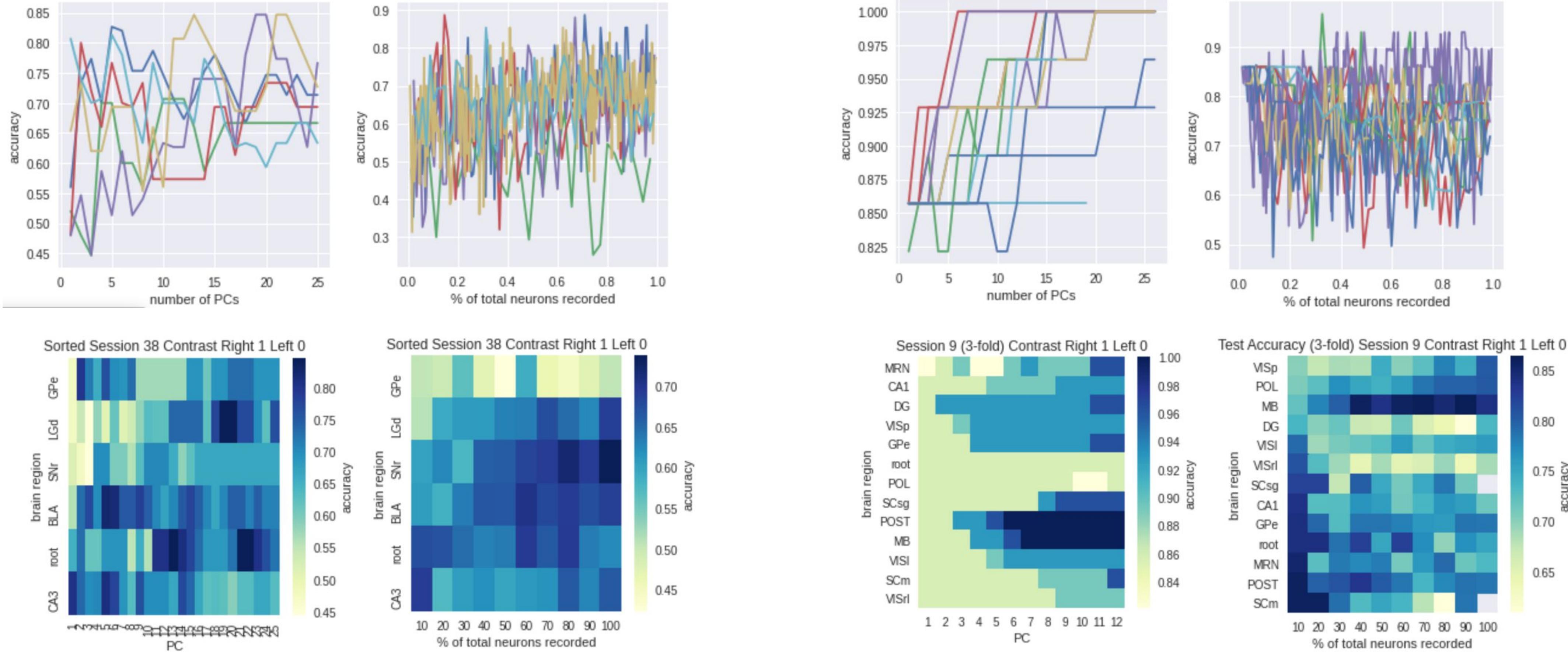


Ameet Rahane



Appendix:

The effect of increasing PCs/neurons on test accuracy varies over sessions and brain areas.



In general, as the number of PCs increased, test accuracy also appeared to increase across the majority of the brain areas. However, increasing the proportion of the total neurons used to train and test the logistic regression model did not necessarily lead to an increase in test accuracy.